PATIENT INVOLVEMENT IN CARE MANAGEMENT PROGRAMS FOR CHRONIC CONDITIONS

by
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ABSTRACT

Background

The World Health Organization sees the increase in chronic diseases as "*one of the greatest challenges that will face health systems globally in the twenty-first century*". Chronic disease affects around 50% of the US adult population, with 25% having multiple chronic conditions. Patient engagement and participation in their own care, are essential for the effective control and management of their conditions. The achievement of patient engagement is multifaceted. It can be affected by access to care, belief and knowledge, provider relationships, provider actions, co-morbidities, and personal and social circumstances. A better understanding of key factors that are associated with a patient achieving engagement would enable interventions to be taken that would increase engagement and ultimately improve care quality and outcomes.

Care management has been advocated as a model of care for individuals with chronic conditions to improve health outcomes and quality of care, through improving care coordination, patient support and self-management. Care management has been found to be associated with better quality and satisfaction in care, but results with respect to cost savings differ, and changes in utilization are mixed. An important aspect in care management participation is understanding how people engage with their care, and the underlying beliefs that would lead to decisions to participate in care programs. For care management to be effective, not only must patients participate but also engage with their care and the health professionals supporting them. What influences a patient's engagement and the resulting outcomes are important to understand in order to ensure care management interventions are appropriately designed and implemented.

Goals and Aims

The overarching goals of this project were to develop measures of patient care management program participation for persons with chronic disease, to gain understanding of the underlying factors and consequences of this participation in order to help improve the care management process.

The specific aims of the study are:

1) To develop an approach for defining and measuring the achievement of patient participation in the care management context;

2) To apply these measurement constructs to determine which individual and organizational factors are associated with patients' active engagement in their own care;

3) To develop a model to predict participation at various stages in the disease management cycle and to estimate the independent effects of participation on care process and utilization; and

4) To create and recommend metrics for the measurement of care management participation across the study populations to enhance understanding of patient groups and sub-populations.

The study population included adult patients during the period September 1, 2009 to December 31, 2012 identified for care management in three Johns Hopkins Healthcare health plans. The study focused on care provided under contract to the managed care plans including primary care, outpatient and inpatient hospital care and care management intervention programs. The study data consisted of administrative health plan data including claims, enrollment files, care management records and patient self-reported data where available. The design was

retrospective, focusing on a population of patients screened for care management across a 3-year period. There were two main dependent variables, enrollment/participation in care management programs and future health expenditure.

A measure of participation, whether an individual enrolled or did not enroll in care management, was derived from claims and care management data during the initial stages of the study. A predictive model was produced from the routine administrative data, utilizing the patient variables associated with participation, to predict future cost and this was validated across all three health plans. A further predictive model was produced with the addition of patient reported variables from the Personal Wellness profile, and created a Care Management Participation Likelihood (CMPL) score based on each of the available consumer reported and administrative variables. Four sub-population "care complexity" groups were created using a modified factor analysis and clustering method. The future (year 2) health expenditures were compared for the care management enrollees against the non-enrollees using two paired matching algorithms.

Findings

Cost reductions were shown overall for the care management enrolled populations across the three plans, with the analysis across the complexity sub-groups showing that the cost reduction was achieved across three of the four sub-groups, with the exception of increased costs for the most complex group. Patients with higher multimorbidity, and older patients, holding other effects the same, were associated with a lower propensity to enroll in care management programs. Higher enrollment in the care management programs (holding other effects the same) was shown therefore in younger and less multimorbid patients. Higher propensity to enroll was

also found in black patients compared to white patients for the Medicare plan. For all plans, members who had been referred to care management also showed increased enrolment. Multi-level (random effects) models were utilized to check that these effects remained when accounting for the higher level regional and case manager effects.

Using two Propensity Scoring methods all three plans showed cost reductions for care management enrollees compared to non-enrollees. The Employee plan showed cost reductions for care management enrollees from $4186.91 to $4486.86 (17.1% - 18.3%), the Medicaid plan showed reduced costs of between $1372.66 and $4074.07 (4.6% - 13.3%), and the Family Health plan showed cost reductions for those enrolled in care management from $2458.51 to $2604.29 (7.3% - 7.7%). The plan populations were further broken down into four complexity sub-groups derived from the factor and clustering analyses, with the lower costs for care management enrolled patients compared to the non-enrolled holding for the three least complex groups, but higher costs for enrolled patients in the fourth most complex group.

Summation

The study, while not seeking to evaluate the current care management programs, provides a measure of participation, individual factors underlying participation, predictive models, and groupings that could be utilized in future program evaluations. The study is of a managed care plan serving multiple populations in Maryland, and while not fully generalizable to all settings, could be expected to inform other managed care organizations in the US and worldwide in other organized delivery systems.

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1 INTRODUCTION

1.1 Project Introduction

The overarching goals of this project were to develop measures of patient care management program participation for persons with chronic disease, to gain understanding of the underlying factors and consequences of this participation and to help improve the care management process.

Accordingly, the specific aims of the study are:

1) To develop an approach for defining and measuring the achievement of patient participation in the care management context;
2) To apply these measurement constructs to determine which individual and organizational factors are associated with patients' active engagement in their own care;
3) To develop a model to predict participation at various stages in the disease management cycle and to estimate the independent effects of participation on care process and utilization;
4) To create and recommend metrics for the measurement of care management participation across the study populations to enhance understanding of patient groups and sub-populations.

1.2 Problem Statement

In 2012 49.8% of US adults had at least one chronic disease, and 25.5% had two or more chronic diseases (Ward, Schiller, & Goodman, 2014). A key component of the care of individuals with chronic diseases is their engagement in appropriate health care services. Currently there is no

clear definition of "engagement" or of the factors that affect whether patients will participate with the healthcare delivery system in the management of their care. For patients with chronic diseases early involvement is an important factor that influences a patient's ability to control and manage their condition (Wagner et al., 2001). For example, the patient must interact with their primary care physician to agree on a care plan, and participate in self-management activities, tests, examinations and prescribed interventions. Care guidelines include a number of recommendations for examinations and tests that are often carried out across multiple providers initiated by patients themselves.

The term engagement has been used to describe the interaction between a healthcare organization and it's patients, in communicating and building a relationship. Patient engagement is multifaceted and can be affected by the access to care, beliefs, provider relationships, provider actions, co-morbidities, personal and social circumstances (Graffigna, Barello, Bonanomi, & Lozza, 2015; Longtin et al., 2010; Powell, Doty, Casten, Rovner, & Rising, 2016). Engagement of an individual can also be transitory, with engagement increasing following signal events, such as a new diagnosis or a hospital admission. Without a meaningful reproducible measure of engagement or participation, other factors related to the care management process may not be well recognized. A better understanding of key factors and their inter-relation with care management participation would likely enable interventions intended to increase engagement and ultimately improve care quality and outcomes.

This study examined patient participation in care management programs. Specifically, participation was measured in two ways: whether a member enrolled in a care management

program following screening; and the duration of continuous enrollment in a care management program.

1.3 Background

The World Health Organization sees the increase in chronic diseases as "*one of the greatest challenges that will face health systems globally in the twenty-first century*" (Nolte & McKee, 2008). In 2012 49.8% of US adults had at least one chronic disease, and 25.5% had two or more chronic diseases (Ward et al., 2014). Chronic diseases lead to many complications, and interact with other conditions such as mental illness to create exacerbations. Major chronic diseases include cardiovascular diseases (heart disease and stroke), cancer, diabetes, arthritis, obesity, and chronic respiratory diseases (asthma and chronic obstructive pulmonary disease). Further, chronic disease co-occurs; the incidence of adults with two or more chronic conditions has increased significantly in the first decade of this century, the estimated number of US adults over 25 with chronic conditions from 2001-2009 rose from 23.4 million to 30.9 million (Ford, Croft, Posner, Goodman, & Giles, 2013). Specific chronic conditions such as diabetes are estimated to affect 8.3% of the population (25.8 million people in the US) and can lead to major complications including heart disease and stroke. Diabetes, for instance, is also the leading cause of kidney failure, non-traumatic lower limb amputations, and blindness in US adults. Chronic conditions also disproportionately affect different populations, such as the African American population (Centers for Disease Control and Prevention, 2009).

A key component of the care of individuals with chronic diseases is their engagement in appropriate health care services. It is important to involve patients early to control and manage their conditions. There is no clear definition of "engagement" with respect to healthcare and the factors that affect whether a patient will or will not engage with the delivery system are still not fully understood. The Baldrige Framework in assessing performance excellence identifies customer engagement as a goal of a successful Healthcare organization, and describes customer engagement as the willingness of patients to seek health services and advocate for those services (The National Institute of Standards and Technology, 2011). Communication, building of relationships with patients, active involvement and satisfaction are factors shown to be associated with engagement.

Care management has been advocated as a model of care to improve health outcomes and quality of care, through improving care coordination, patient support and self-management. Care management can be described by a number of terms that have become synonymous: *disease management*; *case management*; *coordinated care*; *integrated care*; *multidisciplinary care*. (Krumholz et al., 2006). Where, for example, disease management had been usually associated with the care for a specific condition and disease process, increasingly such programs have considered the treatment of comorbid and multimorbid patients. Previous evaluations of care management programs have identified the difficulties that patients have in adjusting their lifestyle to manage their condition; for example, diet (Ibrahim, Beich, Sidorov, Gabbay, & Yu, 2002). Care management has been found to be associated with better quality and satisfaction in care, but results with respect to cost savings differ, and changes in utilization were mixed (Boult et al., 2009; Hong, Siegel, & Ferris, 2014). There is a continuing need to develop programs and

interventions for high need populations, and a need to change culturally to ensure effective communications between interdisciplinary team members and the "*promotion of patient and caregiver engagement in the care process*" (Blumenthal, Chernof, Fulmer, Lumpkin, & Selberg, 2016; Hong et al., 2014).

An important aspect in care management participation is understanding how people engage with their care, and the underlying beliefs that would lead to decisions to participate in care programs. For care management to be effective not only must patients participate but also engage with their care and the health professionals supporting them. What influences a patient's engagement and the resulting outcomes are important to understand in order to ensure care management interventions are appropriately designed and implemented.

2 PUBLIC HEALTH SIGNIFICANCE

The study will develop methods to help understand and define engagement, and to identify patient factors that are associated with the propensity of patients to become actively involved with a health care organization in the management of their health problems. The study, while not seeking to evaluate the current disease management program, does develop and test a measure for participation that could be utilized in future program evaluations.

The study was conducted in a managed care plan serving multiple populations, consisting of an employee health plan, Department of Defense family plan, and a Medicaid plan, and would be expected to inform other managed care organizations in the US and worldwide. The output from the study could be used to help optimize business operations in order to identify the appropriate members for case and disease management services. This would not only apply to those individuals most amenable to such programs, but also to identifying factors associated with poor engagement; allowing future programs to target interventions that offset such factors. The intended study population includes enrollees in a Medicaid health plan, and therefore findings and conclusions would be policy relevant with respect to the Maryland State Medicaid Mandated Managed Care Plan (DHMH, 2002) of which the Johns Hopkins Healthcare (JHHC) Managed care Plan Priority Partners is a part. The factors identified by the study related to participation should provide insight in to whether the care management programs are effectively targeting the at-risk populations, or if programs need to be re-thought to provide greater relevance to specific populations.

3 LITERATURE REVIEW

An important aspect in care management participation is understanding how people engage with their care, and the underlying beliefs that would lead to decisions to participate in care programs. For care management to be effective not only must patients participate but also engage with their care and the health professionals supporting them. What influences a patient's engagement and the resulting outcomes are important to understand in order to ensure care management interventions are appropriately designed and implemented. This section reviews the literature regarding care management participation and patient engagement.

A literature search was undertaken with respect to the term "case management", "engagement", "patient engagement", "participation", and associated Medical Subject Headings (MeSH) term "Self-Management", including and excluding the terms "chronic" and "comorbidity" via online searches of PubMed and CINAHL (Cumulative Index to Nursing and Allied Health Literature) literature databases. Relevant articles were identified that included descriptions of engagement, measures, surveys and frameworks.

Engagement and participation are linked in the literature with multiple concepts, such as self-management/self-care, compliance, self-efficacy, activation, and to the process of communication between patient and providers (Graffigna et al., 2015; Longtin et al., 2010; Powell et al., 2016). These in turn link to the supportive care to patients from care givers, families and the engagement of the providers in supporting patients in designing suitable care plans that are consistent with clinical guidelines. The literature also shows that individual states within the respective concepts are transitory and subject to change over time.

3.1 Overview of Care Management, Engagement and Participation

3.1.1 Care Management

Care management can be described by a number of terms that have become synonymous (Krumholz et al., 2006). These include: *disease management*; *case management*; *coordinated care*; *integrated care*; *multidisciplinary care*. Where for example disease management had been usually associated with the care for a specific condition and disease process, increasingly such programs have considered the treatment of comorbid and multimorbid patients. The types of care models can be categorized by the services that they encapsulate, who is leading the care coordination and care provision, and the patient population being targeted. Boult and colleagues (Boult et al., 2009) undertook a comprehensive review of research showing improvement in quality and outcomes, and identified 15 specific models of care that showed improvements in outcomes. This meta-analysis applied criteria to ensure the research studies used valid data collection methods, analyses, and measures, which significantly reduced the number of articles included in the research from the original literature search. Care management was simply described by Boult et al as a collaborative approach to care involving a nurse or social worker working with the patient and family. Care management was found to be associated with better quality and satisfaction in care, but results with respect to cost savings differed, and utilization changes were mixed.

A report by The Commonwealth Fund (McCarthy, Ryan, & Klein, 2015) categorized coordinated care models according to primary care, hospital to home, at home care, care in

nursing homes, and care in hospitals. The care coordination can also be delivered directly to the patient via nurses, physicians or other health professionals, to individual patients or groups, or indirectly via telephonic or other interactive technology. The report also evidenced the impact of these programs, which vary across a number of quality and outcome domains, highlighting the lack of evidence showing reduction in costs, and concludes the need to ensure proper measurement of programs particularly with a "*already fragmented fee-for-service care system*". A subsequent recent report from Commonwealth Fund highlighted the continuing need to develop programs and interventions for high need populations, referencing the lack of consistent results from comprehensive care models, and in particular emphasizing that changes were also needed culturally to ensure effective communications between interdisciplinary team members and the "*promotion of patient and caregiver engagement in the care process*" (Blumenthal et al., 2016; Hong et al., 2014).

Identifying patients for care management can occur through multiple methods: referrals by physicians, screening statistical algorithms, or patient surveys. Shadmi and Freund (Shadmi & Freund, 2013) advocated multiple combined approaches to avoid bias in selection by the individual methods. Weir et al reviewed three different statistical screening algorithms for the purposes of case selection in the Vermont Medicaid program: Chronic Illness and Disability Payment System (CDPS); Diagnostic Cost Groups (DCG); Adjusted Clinical Groups Predictive Model™ (ACG-PM™) (Weir, Aweh, & Clark, 2008). The costs weights (predictions of future costs) produced by the three systems were used to nominally select patients, with the results compared to the actual second year costs, and found that the ACG system performed best for the lowest 90% of the population and the DCG system performed best for the top 1%. They also

included a comparison of hospitalization predictions and found the ACG system had advantages over the other two systems for the top 10% and 1% at risk populations. In addition to using the risk of high cost and future hospitalization, other measures such as emergency department visits and long stay hospitalizations risk have been advocated for use in patient identification for care management. These other measures were used by Crane and colleagues to screen for at risk of hospitalization for frail elderly patients using the elders risk assessment index (Crane et al., 2010).

With respect to whether patients participate in care management programs when they are offered, the study by Kalsekar and colleagues (Kalsekar, Record, Nesnidal, & Hancock, 2010) analyzing National Ambulatory Medical Care Survey (NAMCS), showed that of patients with at least one chronic condition 21.3% enrolled in disease management programs. The study showed higher enrollment for Medicare and Medicaid compared with other health plans (although they concluded that this was not statistically significant). An earlier study (Lynch, Chen, Bender, & Edington, 2006) had showed a higher rate of initial participation by members of employee health plans who had diabetes in disease management programs (42.1%) but a high attrition rate at 6 months reduced the participation rate to 14.0% and at 12 months to 6.3%. In Australia Hoang and Jones (Hoang & Jones, 2006) investigated whether the uptake rate for disease management programs could be increased using incentives or different approaches (e.g. phone, mail), but concluded these did not lead to significant changes. To be effective in improving health outcomes, single interventions such as education have not been found to be effective on their own, but were effective when employed as part of a range of interventions at multiple levels (Ferlie & Shortell, 2001). A whole systems approach was recommended by Serrano-Gill and

Jacob to improve self-management effectiveness, including information for patients, training clinicians in patient centered care and patient collaboration, and allowing open access to outpatient appointments (Serrano-Gil & Jacob, 2010). With such a multidisciplinary approach voluntary Disease Management Programs have been shown to reduce HbA1C levels in diabetic patients (Ibrahim et al., 2002). However, Gruber (Gruber, 2010) emphasized the importance of patient engagement with their own care, with support from care givers (such as family), if long term favorable outcomes are to be achieved, especially when given the expectation of potentially poor care coordination, differences in the provision of health care plans and provider incentives that are aligned with short term and not long term outcomes.

Care management has been advocated as a model of care to improve health outcomes and quality of care, through improving care coordination, patient support and self-management. A range of measures have been used in studies to examine the outcomes of care management, and a range of factors have been identified the are potential confounders when comparing outcomes between different populations. Frank and Epstein (Frank & Epstein, 2014) concluded that younger patients under the age of 65 with higher costs due to major multimorbidities such as mental health conditions, would benefit from care management programs, particularly in respect to coordination of care between mental health services, substance misuse and rehabilitation services. Higher costs were linked to higher emergency department visits and inpatient hospitalizations. This was also reflected in the analyses of a diabetes disease management program in Louisiana also showed lower emergency department visits for patients, and furthermore that uninsured patients increase their use of emergency departments, adjusting for

gender, age, previous hospitalizations and comorbidity (Chiou, Campbell, Horswell, Myers, & Culbertson, 2009).

In evaluating a care management model, quality of care was reviewed with respect to a "Guided Care" model by Boyd and colleagues (Boyd et al., 2010) concluding that patient reported ratings of care quality after 18 months was higher for those who had received the nurse care management intervention, compared to those who were receiving usual care, in particular with respect to care coordination and decision support. Berthold and colleagues (Berthold, Bestehorn, Jannowitz, Krone, & Gouni-Berthold, 2011) found some of the intermediate outcomes for a diabetes management program improved, such as cholesterol, this was not found in a range of other measures which did improve over time but this improvement could not be directly attributed to the program. This study also highlighted the potential issues of confounding, when such disease programs are part of a national implementation (in this case in Germany).

3.1.2 Engagement: self-management and efficacy

Serrano-Gill and Jacob (Serrano-Gil & Jacob, 2010) discussed the importance of engagement and empowerment of patients with chronic a chronic disease (type 2 diabetes) to self-manage. A randomized control study in Wisconsin showed that while the clinical care met recommended guidelines (Helstad, Wiegmann, Camponeschi, Udlis, & Meredith, 2004), the patients were inconsistent in their self-management. Individual factors not related to the clinical treatment such as age and education level had been found to be related to the control of diabetes (Nerenz, Repasky, Whitehouse, & Kahkonen, 1992), thereby demonstrating the need to understand the

efficacy of patients as well as the compliance of health care providers to guidelines and complexity of treatments. Engagement in specific self-management behaviors such as glucose checks, diet monitoring, exercise and smoking, has been studied with respect to diabetic patients. The study investigated the differences by race and ethnicity, an issue relevant to diabetes as a condition that disproportionately affects the non-Hispanic black population when compared to non-Hispanic whites (77% higher risk of diagnosis). There were results in different patterns of utilizations with black and Hispanic patients in disease management programs showing higher levels of hospital visits but lower use of preventative services than white patients (Oster et al., 2006). The role of the providers as a support to patients was found to be crucial, in ensuring that patients engage in the management of their care, and in instilling self-efficacy in undertaking self-management activities across different socioeconomic groups (race, ethnicity and health literacy) (Greene, Yedidia, & Take Care to Learn Evalutation Collaborative, 2005; Sarkar, Fisher, & Schillinger, 2006).

A review of engagement in self-management by patients with disabilities emphasized the importance of informed decision making, particularly in selecting providers, and the use of information provided by professionals (Lakhani, McDonald, & Zeeman, 2016). Another review emphasized the increased importance of social networks to support self-management for chronic illness, the importance of being able to navigate networks and the personal and collective influences and beliefs that underpin "*collective efficacy*" (Vassilev, Rogers, Kennedy, & Koetsenruijter, 2014). The importance of utilizing information technology by diabetes patients has been highlighted by studies that have also assessed the level of engagement in therapeutic care plans and a variety of self-management activities (Glasgow, 2010; Grant et al., 2006). Five

concepts related to patients engaging in self-management ("*self-care"*) were identified by Blickem and colleagues (Blickem et al., 2011): awareness of alternative self-management activities; previous use of information; ability to self-manage; opportunities to self-manage; and "*congruence and synergy*" with the provider.

3.1.3 Patient Engagement: Compliance and Participation

Lindenmeyer and colleagues (Lindenmeyer, Whitlock, Sturt, & Griffiths, 2010) reported two types of behaviors with respect to self-management by diabetic patients. Patients who strictly incorporating the recommended interventions into their daily life (such as diet changes) or who were applying the recommendations flexibly and where manageable. Wallace (Wallace, 2010) identified four categories of patient from providers' perspectives, related to patients' level of engagement with the management of their diabetes. Patient engagement was described as the active participation with the provider to plan the management of their diabetes, and seek to follow the provider's recommendations ("compliance"). The level of engagement labels Wallace used were as follows: 1) patients who follow the recommendations of their providers ("Autopilot"); 2) those who are active and then become inactive in their management ("Off and On"); 3) those who placed a low priority on the management of their diabetes due to other priorities such as multi-morbidities ("Back Burner"); 4) and patients who are actively engaged in their own management but will be selective in following the recommendations from their provider and seek alternative treatments ("Wonder Juice"). Similar characteristics of this latter group were also identified in a study by Dettalo and colleagues, who identified the characteristics of patients who completed chronic disease self-management programs, and found a cohort of

individuals who were dissatisfied with their primary care providers and were seeking alternative self-management education (Dattalo et al., 2012). The issue of provider compliance was discussed, recognizing the low level of compliance overall, and that the engagement of providers themselves can be an issue for patients where there were incomplete examinations and consideration of patients' circumstances. These four categories reflect to an extent the five concepts, identified above by Blickem and colleagues, that underlie patients' engagement in self-management activities. The American Diabetes Association (ADA) recommends a number of activities that require the compliance and participation of the patient and provider, for monitoring, examination and control purposes. In addition to the differences noted previously by race and ethnicity in the uptake of self-management activities, disparities have also been reported in the healthcare provision attributed to issues such as provider adherence to clinical guidelines and lack of trust in providers (Greene et al., 2005; Kirk et al., 2005).

3.1.4 Activation and empowerment

In addition to the self-management and compliance concepts raised above, the interaction between patient and provider are important to facilitate engagement. Studies have highlighted the importance of a style of communication that is attentive, respectful and committed (Warmington, 2012), and enables the patient to progress through a "D*ecision-making continuum"*, consisting of *participation, activation and empowerment* (Roter, 2000). These studies show that patient engagement can therefore be expressed in respect of the relationship with the provider, whether passive or active, leading to a level of activation and participating in the care process and self-management. Concepts such as race and gender concordance may be important in understanding

the relationships and socioeconomic differences already noted. These processes provide concepts that are distinct from compliance and indeed advocate styles of engagement where a patient is not necessarily compliant with a provider, but an empowered patient would necessarily be actively managing and problem solving, with the provider supporting the patient in their decisions.

3.1.5 Summary of Care Management, Engagement and Participation

Previous research shows that engagement and participation are linked with multiple concepts in the literature, such as self-management/self-care, compliance, self-efficacy, activation, and to the process of communication between patients and providers. These in turn link to the supportive care to patients from care givers, families and the engagement of the providers in supporting patients in designing suitable care plans that are consistent with clinical guidelines. The literature also shows that individual states within the respective concepts are transitory and subject to change over time.

Care management is now synonymous with multiple models of integrated and comprehensive care, but the results of reviews are mixed. While studies have shown improvement in quality of care and patient satisfaction, the evidence for costs savings are not consistent. The understanding of underlying patient factors is not well described, or the description of patient sub-populations of interest.

This study seeks to utilize routine data to derive measures of participation; it will attempt to add to the literature by providing an exploration of the patient factors that underlie and effect participation in care management across different populations, by providing new models to predict participation, and provide a methodology to review the outcomes of patients who participate and those who do not, and which sub-populations are of particular interest.

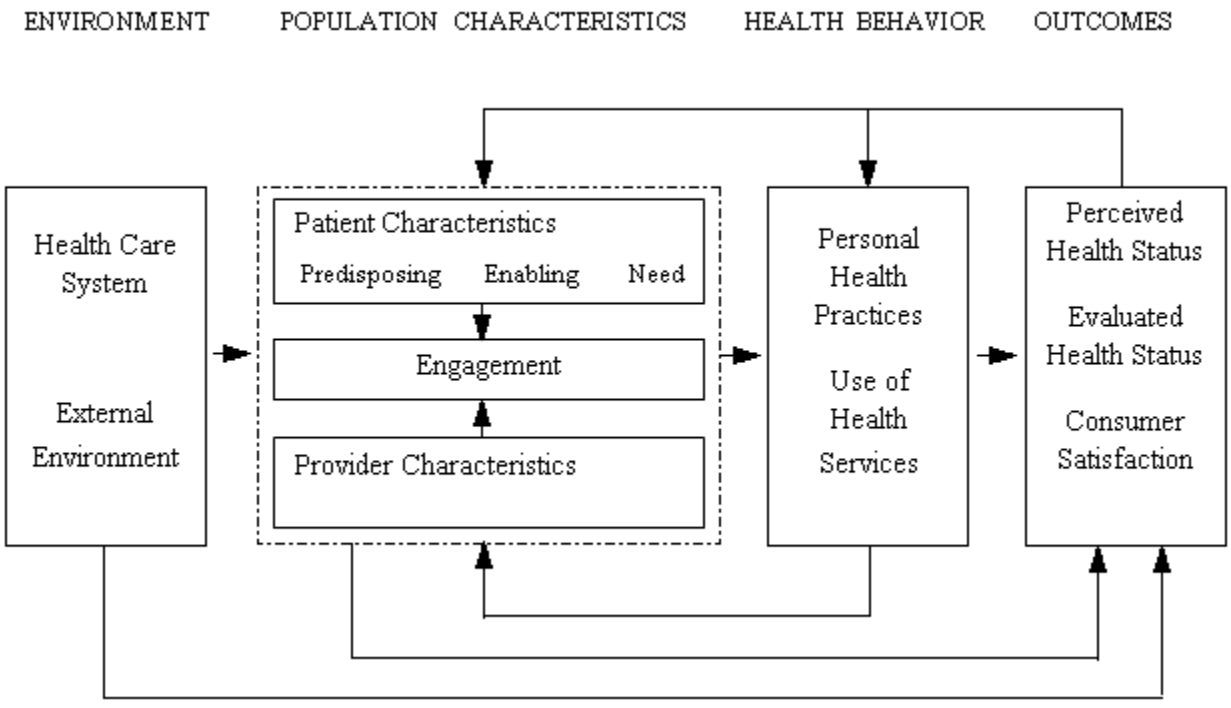
3.2 Conceptual Framework

To understand the relationship between behaviors associated with engagement and participation, and the patient's costs and utilization of services, two frameworks were identified, the PRECEDE-PROCEED framework (Green & Kreuter, 1999) and the behavioral model and access to medical care developed by Aday and Anderson (Andersen, 1995).

The PRECEDE-PROCEED framework provides a model to understand the behavioral constructs and factors associated with engagement. This model was applied to self-management of diabetes by Gielen and colleagues (Gielen, McDonald, Gary, & Bone, 2008) who described the predisposing, reinforcing and enabling factors resulting from educational strategies. They showed these factors in turn lead to certain behaviors which interact with environmental factors (such as the health plan) and give rise to the health problems and clinical markers associated with the diagnosis and management of diabetes. A number of the constructs in this framework were reflected in the findings of Sousa et al (Sousa, Zauszniewski, Musil, McDonald, & Milligan, 2004) who concluded that self-care and engagement in self-care were associated with a patient's *knowledge, social support, self-care agency, and self-efficacy*.

The behavioral models developed by Aday and Andersen were originally developed to aid in the understanding of health services by families, and subsequently developed as an individual behavior model (Andersen, 1995). The framework represents the external environmental influences and population characteristics (both individual and provider) that underlie health behavior and utilization of health services leading to outcomes (such as health status and satisfaction). Figure 3-1, shows the model adapted with the inclusion of the engagement between the provider and patient that leads to the health practices undertaken by the patient and to the use of health services. This provides for the engagement to be not only a patient issue, sometimes described as compliance by providers, but also be applied to the providers in their interaction with patients through the provision of support (Greene et al., 2005).

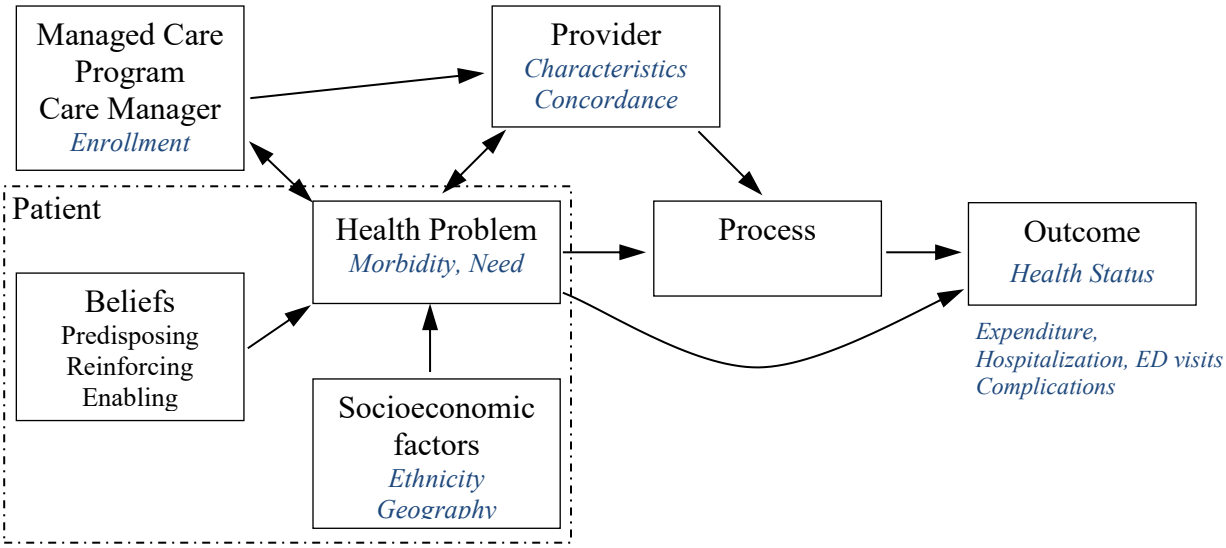
Figure 3-1: Healthcare Utilization and Conceptual Model*



* Adapted from Aday and Andersen (Andersen, 1995)

Figure 3-2 below, is a conceptual model showing the relationships between the patient, provider, care manager and care plan, the beliefs and socioeconomic factors influencing the patient that together with the patient's existing health measures give rise to the processes of care utilized by the patient (such as routine examinations and test). The process of care leads in turn to patient outcomes such as changes in health services utilization (healthcare expenditure, rates of hospitalization or emergency department visits), incidence of complications, or health status. The relationship with the provider and the effect of provider behaviors, such as adherence to practice guidelines (provider compliance) and collaborative approaches to working with the patient, are an important input to the patient's own engagement, participation and adherence to self-management. These beliefs, personal health factors and interactions with others lead to the patient undertaking processes such as testing, examinations and treatments, which in turn leads to outcomes with regard to the patients' health status.

Figure 3-2: Patient, Provider and Care Management Interactions: A Conceptual Model



This study seeks to measure participation ("Enrollment") in care management programs, by identifying the association of patient factors such as morbidity, race/ethnicity, and region/geography. The process of patient participation or non-participation (when controlling for patient effects), would be expected to lead to changes in patterns of utilization which in turn lead to changes in intermediate outcomes such as health expenditures, rates of hospitalization and emergency department visits. The providers of health care services, the care managers, and enrollment of patients in a health plan are potential modifying or confounding effects in the measurement of participation.

4 METHODS AND RESEARCH DESIGN

4.1 Study Aims, Objectives, Questions and Hypotheses

The overarching goals of this project were to develop measures of patient care management program participation for persons with chronic disease, to gain understanding of the underlying factors and consequences of this participation and to help improve the care management process. The project specific aims and associated study objectives are presented below.

Aim 1 - Defining and Measuring Participation

Aim 1: To develop an approach for defining and measuring the achievement of patient participation in the care management context.

Aim 1 Study Objectives:

1.1 To derive an operational definition, constructs and a potential measurement framework of "patient engagement" in the care management context utilizing the scientific and gray area literature and input from key informants and experts.

1.2 To test the feasibility of deriving alternative measures of participation using available secondary data and patient reports from available surveys.

1.3 To undertake measurement analytic activities (including factor analysis) to assess the properties of alternative measures (e.g. construct and predictive validity and reproducibility).

Aim 2 - Factors associated with Participation

Aim 2: To apply these measurement constructs to determine which individual and organizational factors are associated with patients' active participation in their own care;

Aim 2 Study Objectives:

2.1 To identify individual patient related factors which are independently associated with levels of patient participation in care management activities.

2.2 To identify organizational and provider related factors which are independently associated with high levels of patient participation in care management activities.

Aim 3 – Predicting Participation

Aim 3: To develop a model to predict participation at various stages in the disease management cycle and to estimate the independent effects of participation on care process and utilization;

Aim 3 Study Objectives:

3.1: To develop and test a model that will predict which individual patients will likely participate at initial and subsequent stages of the care management process. Based on the results of analyses in Aims 1 and 2.

3.2: To assess the independent relationships between patient participation and outcomes such as health expenditures, and health services utilization.

Aim 4 - Initial Implementation and Assessment

Aim 4: To create and begin the dissemination of tools for the measurement of care management participation across the study populations to help improve the care management process.

Aim 4 Study Objectives:

*4.1: To begin to v*alidate the outputs of the predictive model(s) and assess potential benefits of the models, by qualitative interaction with JHHC experts.

4.2: Provide preliminary analysis to JHHC care management staff by using the constructs and metrics derived in the study, including an analysis of sub-population patient groups of interest.

4.2 Study population

The study population consisted of adult patients with chronic diseases from three Johns Hopkins Healthcare (JHHC) health plans who were screened for care management enrollment from September 1, 2009 to December 31, 2012. JHHC has three programs: Johns Hopkins Employer Health Programs (EHP), Priority Partners (PP), and Johns Hopkins US Family Health Plan (USFHP). The study subjects are the adult members of managed care plans who were screened for seven types of care management programs, from the EHP, PP and USFHP plans: Population

Database 84.6%; Maternity 5.3%; HIV/AIDS 4.1%; Omega Life 3.1%; End Stage Renal 1.5%; Asthma 0.8%; Guided Care 0.5%. Following screening the patients were invited to enroll in the care management programs and either accepted or declined to enroll.

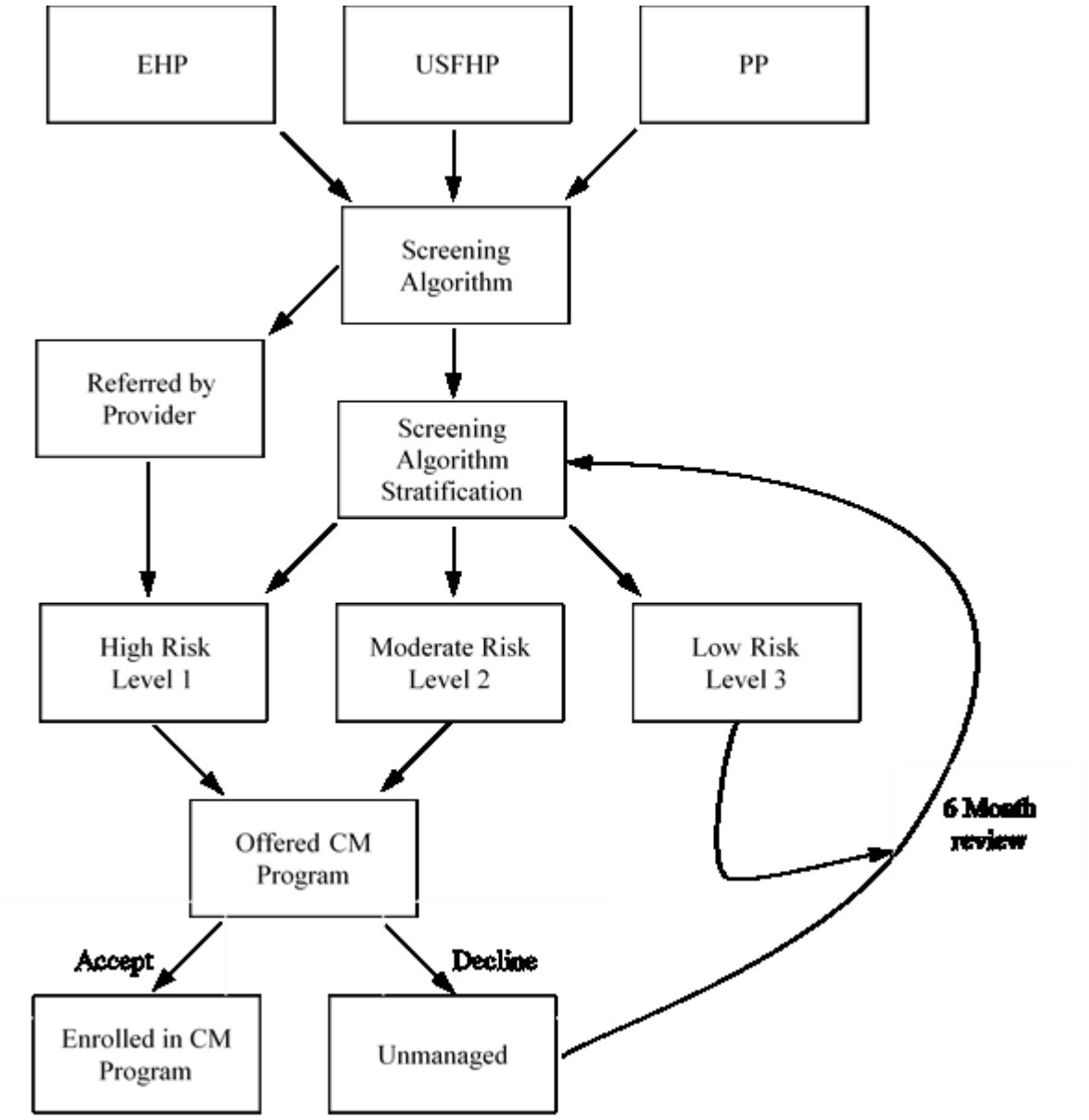
At the time of the study JHHC had in excess of 250,000 members across multiple plans EHP, Priority Partners and US Family Health Plan (JHHC, 2011). EHP is a self-funded health plan for employees and families with approximately 50,000 members in the Maryland, Pennsylvania and North Virginia area. Priority Partners is one of seven Managed Care Organizations (MCOs) providing healthcare to individuals under the Maryland Medicaid children and adult programs. The USFHP is a managed care plan contracted with the Department of Defense to serve members of the armed services, their families, retirees and survivors.

Care management programs within Johns Hopkins Healthcare utilize screening algorithms to identify high risk patients. The algorithms consist of clinical criteria and predictive modeling, with general and condition-specific criteria being applied (Murphy, Castro, & Sylvia, 2011). The JHHC program makes use of the Adjusted Clinical Groups Predictive Modeling (ACG-PM) system, which utilizes administrative claims data to create a risk prediction of individuals with high future health expenditures or likelihood of hospitalization (Weiner & Abrams, 2009). The claims data identifies diagnoses and pharmacy recorded for patients, but does not include clinical data, such as tests, examinations and findings.

The study setting included all care provided either by the Johns Hopkin Health System (JHHS) or other organizations and paid for by JHHC, including primary care, outpatient and inpatient

hospital care, retail pharmacy, and special care management intervention programs. The population included patients of the three health plans who were over the age of 18, and were identified as having a high or moderate need for care management through the JHHC screening algorithm or referred for care management. A referral can be made by care providers, clinicians within JHHC, or patient self-referral, with clinical screeners checking the screening criteria are met for care management. Figure 4-1 JHHC Care Management (CM) Screening Algorithm depicts the process JHHC uses to risk stratify members into three groups (High, Moderate and Low). Those classified as "high" or "moderate" are offered enrollment into a care management program. The JHHC screening uses predictive risk scores (derived from the ACG-PM), with "moderate" risk adults with a score approximately in excess of 0.44 and "high" risk over 0.75 in the Priority Partners program (PP) during the study period. For the Johns Hopkins Employer Health Programs [EHP] the risk score thresholds were approximately 0.18 for 'moderate' and 0.31 for 'high' risk adults. Those stratified as "low" or declining enrollment in the program are reassessed as part of an ongoing six-month re-review cycle.

Figure 4-1 JHHC Care Management (CM) Screening Algorithm



4.3 Study Design

The study utilized administrative health plan data (i.e. claims and enrollment files), with sub-groups of patients having additional data available from two other sources: care management administrative data and patient self-reported data. The study was a retrospective design, focusing on a population of patients screened for care management across a 3-year period (September 2009 to December 2012). The study consisted of data exploration and the creation of logistic regression models, with patient participation (care management program enrollment) as the key dependent variable.

A literature review was undertaken to establish currently recognized definitions and related concepts, such as self-management, activation, participation, compliance and "readiness to change." These definitions were discussed with clinical and administrative colleagues representing a multi-disciplinary team to review relevant constructs, utilizing the PRECEDE-PROCEED model as a framework (Green & Kreuter, 1999).

Participation markers were created from the administrative data at patient level consistent with the definition of participation, as described above. De-identified patient level data were extracted for all adult patients, including both those who did or did not enroll in the JHHC Care Management program.

4.4 Variables and measures

For the different phases of the study two main dependent variables were used. First was the level of participation, second was the future health expenditures and utilization. A measure of

participation was derived from claims and clinical test data (see variable list in appendix 8.1). Participation was represented as a dichotomous variable, and also tested as an ordinal or semi-continuous variable classifying the duration and type of participation. The participation variables were developed during the initial stages of the study. As a new measure they were subjected to a design, test and refinement process including the testing of construct validity, internal reliability (Cronbach's alpha), responsiveness, validity and interpretability (Juniper, Guyatt, & Jaeschke, 1996). The future health expenditure variable was an aggregation of costs attributed to individual patients over continuous 12-month period, in the second year following the screen process and the data utilized as independent variables.

A potential threat to validity of any measures is the reliance on utilization and cost as a dependent measure and at the same time measures derived from visits (e.g. intensity of services) used as an independent measure. This could create a potential overreliance or circularity in a measure, such that historic utilization leads to future utilization directly, rather than being determined by patient factors. To mitigate against such potentially confounding effects, independent variables were explored for models with and without the inclusion of (prior) cost.

The intermediate control variables include the health risk variables, morbidity measure (ACG), age, gender, health plan type, duration of plan eligibility, social/economic status, ethnicity/race and Primary Care Provider (PCP) involvement. The characteristics of the enrollment in the care management dependent variable.

For aim 4, to help assess the potential impact of participation in care management, an analytic model focusing on expenditure and types of utilization in the succeeding (following screening) year was derived. The variables of interest include participation, utilization of medical services, and the clinical risk variables created by the ACG-PM system.

The regression coefficients from the logistic regressions used a series of ACG derived morbidity measures. These were expected to show the increased effects on patients with multiple and major morbidities. The importance of interaction between certain variables was also investigated with the expectation of major morbidities concerned with different body systems (disease processes, major comorbidities) to show a multiplier effect rather than additive effect. Individual factors, provider effects, participation and case management effects were investigated using multi-level (random effects) models. The levels of resources utilized by individuals are related to the extent of their comorbidities and subsequent health needs. To help mitigate against this effect when measuring impact of resource utilization on levels of engagement, the Johns Hopkins ACG system was be utilized as a validated approach to help control for morbidity burden (Starfield, Weiner, Mumford, & Steinwachs, 1991).

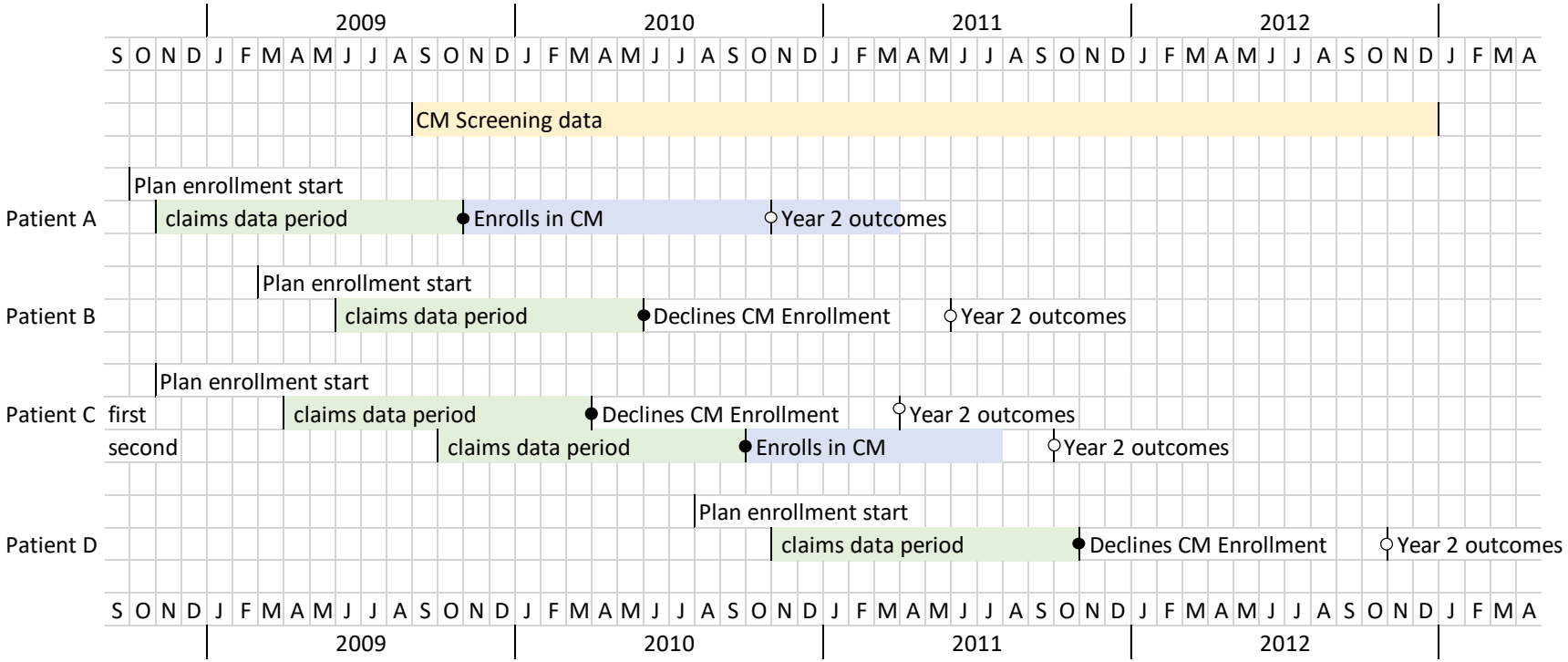
4.5 Methods of data collection

The subjects were identified via the JHCC members' database, for all adult patients who had either been referred for care management by a clinician, or had been categorized as "high" or "moderate" risk through the JHHC care Management screening algorithm. JHHC has access to claims data and other personal health information for the members of its three health plans: EHP, Priority Partners, US Family Health Plan. The data were obtained electronically for adult

members of all three health plan. These electronic files included claims data, care management administrative data, plan enrollment dates, patient reported data occurring during the three-year time-frame.

Figure 4-2 is a depiction of the data collection process, showing four example patients. The individuals for the study were identified from care management (screening) administrative data from September 1, 2009 through to December 31, 2012. Patient A was screened for CM in November 2009, and enrolled in the CM program. Base level independent variables were taken from the ACG data representing claims from the previous 12 months, plan enrollment data, and the year 2 outcome measures were derived from November 2010 claims data (12 months following enrollment). Patient B, who did not enroll in a CM program, had data collected in the same way: claims data from June 2009 to May 2010; declines CM enrollment in June 2010; and year 2 outcome measures from June 2011. Patient C had two events during the study time period, the first in April 2010 was a decision not to enroll in CM with outcomes measured 12 months later, and the second event in October 2010 was a decision to enroll in CM, with a second set of outcomes in October 2011.

Figure 4-2 Data collection timeline



4.6 Analytic approach/Analysis Plan

Concepts and constructs of engagement were derived from a literature review, subjected to review and validation by an expert panel and refined. The analysis consists of data exploration, production of descriptive statistics, development of measures, development and testing of regression models. The development and testing of the predictive models was designed to follow the TRIPOD (Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis) recommendations and examples, specifically with respect to model comparisons, internal and external validation of the models, and describing the model calculations (Collins, Reitsma, Altman, & Moons, 2015; Moons et al., 2015).

The data analysis sought to identify factors associated with engagement and create a predictive model of likelihood to participate. An initial exploratory data analysis was undertaken to provide information on the distribution of independent variables at baseline, 12 months and 24 months. The participation variables and enrolment variables were analyzed as dependent variables with analysis of covariance with other variables to test for potential confounding due to the quasi-experimental design of the study (Streiner & Norman, 2008). Logistic regressions were undertaken with respect to individual factors (demographic, ethnicity, age, gender, and pre-test disease status) to identify those associated with participation and enrollment. Additional logistic regression (random effects models) was undertaken after the addition of system level and care related variables, to provide a full assessment of our ability to predictive participation.

The logit model applied to the data can be expressed as

$$log\frac{P_{success}}{1-P_{success}} = Intercept + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

$$P_{success} = \frac{e^{Intercept+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k}}{1+e^{Intercept+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k}}$$

Where $P_{success}$, is the probability of success, e.g. probability of enrollment in care management program. β_k is the weight (estimate) for dependent variable X_k.

4.7 Analytic Objectives by Aim

Following each aim study objectives are reiterated and the analytic approach used to address each aim is discussed.

Aim 1 - Defining and Measuring Participation

Aim 1: To develop an approach for defining and measuring the achievement of patient participation in the care management context.

Aim 1 Study Objectives:

1.1 To derive an operational definition, constructs and a potential measurement framework of "patient engagement" in the care management context utilizing the scientific and gray area literature and input from key informants and experts.

1.2 To test the feasibility of deriving alternative measures of participation using available secondary data and patient reports from available surveys.

1.3 To undertake measurement analytic activities (including factor analysis) to assess the properties of alternative measures (e.g. construct and predictive validity and reproducibility).

A literature review was conducted to identify definitions of engagement, and to explore existing behavioral and health services research models to derive a summary of concepts and constructs potentially related to engagement. The concepts and constructs identified through a literature review were subjected to review by clinical and administrative colleagues in JHHC.

The current literature describes patient engagement with respect to concepts of care management, self-management and efficacy. Whilst engagement has been associated in the literature with patients' compliance and adherence, these are also provider attributes. The level of participation of both patient and provider in the care management process leads to activation and empowerment of the patient. Clinical and administrative colleagues provided input to the understanding of engagement and the importance and relevance of constructs derived from the literature review and their relationships.

Potential measures of participation were derived from the available secondary data, using data markers consistent with participation and advice from the expert panel, such as care management

enrolment, and duration of enrolment. A data exploration was undertaken to consider the completeness and validity of associated data items. Potential measures considered included the creation of dichotomous and categorical markers based on single variables, or composite measures based on multiple variables as nominal and ordinal scales.

Exploratory Factor Analysis (EFA) was used to identify variables associated with engagement, and reduce the number of variables being considered (Joliffe & Morgan, 1992). This technique derives "loadings" for factors associated with level of variation within a measure attributed to each distinct factor. An initial model was derived through maximum likelihood estimation, with refinement using an analysis of the covariance of the variables. Results were shared with the expert panel to access content validity of the identified factors, specifically whether the factors cover the attributes and constructs related to engagement. A logistic regression with enrollment of individuals as the dependent variable was then used to identify variables associated with participation.

Exploratory data analysis and the creation of descriptive statistics informed the utilization of the additional administrative data. Particular attention was paid to the completeness and consistency of key variables identified from the factor analysis. The measure of participation patterns of utilization were categorized to act as intermediate variables to stratify the analyses. The categories were both tested as a dichotomous variable consistent with routine and non-routine utilizations of health services, and as categorical variables reflecting different patterns of hospitalization, ER and ambulatory visits.

The potential measures were subjected to measurement analytics to test construct validity, internal reliability (Cronbach's alpha), responsiveness, validity and interpretability. A further stage of expert review was undertaken to test content validity and suggest the addition or omission of variables.

Aim 2 - Factors associated with Participation

Aim 2: To apply these measurement constructs to determine which individual and organizational factors are associated with patients' active participation in their own care;

Aim 2 Study Objectives:

2.1 To identify individual patient related factors which are independently associated with levels of patient participation in care management activities.

2.2 To identify organizational and provider related factors which are independently associated with high levels of patient participation in care management activities.

Two methods were used to identify factors associated with participation: Logistic regression; and Exploratory Factor Analysis (EFA).

Logistic regression models were initially designed using all available independent variables, with the resulting odds ratio for each variable demonstrating the potential association with the dependent variable ("participation"). Further refined models were produced by using stepwise

regressions to reduce the number of variables. In order to investigate effects that were not necessarily at the patient level, multilevel mixed models (i.e. Random Effects Models) were utilized. Random effects models were chosen as they incorporate heterogeneity of the effects and so do not assume homogeneity (DerSimonian & Laird, 1986). In this context we were not primarily interested in the actual differences in the group level variable (e.g. specific differences attributable to each region, or individual nurse care managers), instead we were interested in whether between-group differences were significant compared to within-group differences. That is, whether the level of participation can be attributed to the care manager level or region level, rather than to the patients (Rosner, 2006). Models were created using region and individual care managers as group or global effects, these multi-level random effects models were then tested against the null model (i.e. the base model not grouped by region or care manager) for significance. This was done by comparing the ratio of likelihoods for the respective models (SAS procedure COVTEST, (SAS Institute Inc, 2009)).

Exploratory Factor Analysis (EFA) was used to identify variables associated with engagement, and to potentially reduce the number of variables being considered (Joliffe & Morgan, 1992). This technique derives loadings for factors in describing the level of variation within a measure attributed to a given factor. An initial model was derived through maximum likelihood estimation, with refinement using an analysis of the covariance of the variables. Results were shared with the expert panel to access content validity of the identified factors, specifically whether the factors cover the attributes and constructs related to engagement. A logistic regression with enrollment of individuals as the dependent variable was derived to identify variables associated with enrollment.

A factor analysis was undertaken with SAS (SAS Institute Inc, 2010) to review the selected items, using the approach utilized by Bower and Colleagues (Bower, Mead, & Roland, 2002). This approach assumes that are there are unmeasured latent variables (factors) that underlie the observed variables. This method was utilized to both explore the reduction of input variables to a measure, to inform the theoretical framework and assess the construct validity of a measure derived from the observed variables.

Jones described methods including the reduction of variables using factor analysis, with the creation of patient clusters based on a Hierarchical Cluster Analysis (Jones, 2009). This approach was further adapted using Variable Cluster Analysis (SAS Procedure VarClus) as described by Liau and colleagues (Liau, Tan, & Khoo, 2011). In addition to ordinal variables, dummy dichotomous variables were created and subjected to cluster analysis to provide potential aggregated variables. This led to an iterative approach of combining variable values from the cluster analysis.

Aim 3 – Predicting Participation

Aim 3: To develop a model to predict participation at various stages in the disease management cycle and to estimate the independent effects of participation on care process and utilization;

Aim 3 Study Objectives:

3.1: To develop and test a model that will predict which individual patients will likely participate at initial and subsequent stages of the care management process. Based on the results of analyses in Aims 1 and 2.

3.2: To assess the independent relationship between patient participation and outcomes such as health expenditures, and health services utilization.

The analysis consisted of exploratory data analyses, production of descriptive statistics, development and testing of regression models, and the application and testing propensity score matching. Two basic types of regression models were created, linear and logistic regression. The respective models were validated using split sample model validation.

Exploratory data analysis and the creation of descriptive statistics were derived to inform the utilization of the claims and administrative data. Particular attention was paid to the completeness and consistency of key variables identified from the factor analysis, thus ensuring that such variables were relevant to the population and minimize susceptibility of the variables to selection bias. For example, whether such variables had valid values recorded for most of the study population, rather than being missing or incomplete. Sub-population characteristics (multi-morbidity complexity, and screening characteristics) were categorized to act as intermediate variables to stratify the analyses. The categories were analyzed across all three health plan sub-groups, for patients enrolled and not-enrolled in case management, for outcomes in the second

year following screening. The second year outcome measures assessed were mean annual health expenditure, mean number of hospitalizations, and emergency room visits.

Previous studies of healthcare costs identified the analytic challenge of the cost distribution being highly right skewed and following a lognormal distribution (Diehr, Yanez, Ash, Hornbrook, & Lin, 1999). To help address this Log transformed charges are sometimes used for the purposes of models for risk stratification for disease management programs (Li et al., 2005).

To help assess variables to potentially be added to the logistic model the likelihood ratio test was applied to candidate models. The creation of parsimonious multiple linear regression models would be undertaken as using forward and backward stepwise regression. Selected variables for models were assessed for collinearity and whether the assumptions of any regression models hold. Interaction terms were added to the models to test for significant effect modification with models compared using the Akaike information criterion (AIC) (Bozdogan, 1987). Receiver Operating Characteristic (ROC) analysis was used to identify optimal models with respect to sensitivity and specificity.

A Score model was derived from the final model, by creating a for each of the input variables using the points method described by Sullivan and Colleagues (Sullivan, Massaro, & D'Agostino RB, 2004) originally developed by the Framingham Heart Study. A score is calculated for each variable in the model by dividing the regression estimate by a constant value representing the value of a single unit, and rounding to the nearest integer. This tool was developed to aid calculation and decision making by clinicians.

While testing the outcomes following case management enrollment, it is necessary to reduce the risk of selection bias where possible to ensure that the observed outcomes are associated with the enrollment. Ideally a study would be randomized but in an observational study within an operational setting randomization of cases to "treatment" and "control" groups is not possible. The propensity score matching (PSM) approach was therefore used as a retrospective proxy for randomization to help control for bias. When observing the outcomes for patients who have either enrolled ("treatment") or not enrolled ("control") in to care management, there may be differences in these outcomes, but we cannot necessarily conclude that these differences in outcomes are as a result of the care management or because of inherent differences in the characteristics of the two populations (Coca-Perraillon, 2007; Kleinman, 2010). Propensity score matching (PSM) identifies patients that have similar characteristics, e.g. similar probability of enrollment, and therefore similar independent variable values such as age, gender, and morbidity pattern. A key assumption in the PSM approach is conditional independence. This is that there are is a given set of covariates which are observable, not affected by the intervention, and the outcomes are independent of the assignment to 'treatment' or 'control' (Caliendo & Kopeinig, 2008). Specifically, any variables that affects an individual enrolling in care management and subsequent outcomes, are included in the model, and therefore, there are no unobserved variables affecting enrollment. The analysis was then performed on the matched pairs of cases, on the assumption that the enrolled and non-enrolled matched cases will have similar underlying characteristics based on the sub-populations having similar distributions for the probability of enrolling, retrospectively creating randomized controls.

In order to implement PSM, the PSMatching SAS macro developed by Coca-Perraillon was used. This macro searches for and creates a table of treatment-control pairs. The "Nearest Available Neighbor" and "Caliper" matching methods were used without replacement (i.e. controls were only used once), where all of the cases are randomly sorted. PSM was carried out separately for each of the three plans, first using Nearest Neighbor matching and then using the Caliper method. In the Nearest Available Neighbor method for each treatment case the control is chosen that had the closest propensity score (probability of enrollment in case management), this method ensures a control match for each treatment case, but does not ensure that the absolute difference in score are close. The Caliper method allows for a minimum absolute difference in prevalence to be specified, but does result in data loss where a match cannot be found within the specified absolute difference (Coca-Perraillon, 2006). Caliper matching has been found to have less bias than Nearest Neighbor and other propensity matching methods, but Nearest Neighbor produces better estimates due to producing a greater number of matched pairs (Austin, 2014).

Aim 4 - Initial Implementation and Assessment

Aim 4: To create and begin the dissemination of tools for the measurement of care management participation across the study populations to help improve the care management process.

Aim 4 Study Objectives:

*4.1: To begin to v*alidate the outputs of the predictive model(s) and assess potential benefits of the models, by qualitative interaction with JHHC experts.

4.2: Provide preliminary analysis to JHHC care management staff by using the constructs and metrics derived in the study, including an analysis of sub-population patient groups of interest.

The measure of participation and predictive model are to be compared to the results of applying the existing algorithm to a test population of patients. A performance comparison was undertaken using the c-statistic, and measures of sensitivity, specificity and positive predictive value (PPV) (Murphy et al., 2011). Sensitivity and specificity measures are inversely related and so the maximization of sensitivity (increasing likelihood of selecting a true positive, reducing false negatives, lowering type II errors) will typically lead to a reduction in specificity (increasing type I errors). The number of individuals selected by the algorithm should also be a consideration with respect to the capacity of case managers to review.

The outcomes analysis, using Propensity Score Matching was broken down by sub-population patient groups derived from the exploratory factor analysis and variable cluster analysis, and provided to colleagues in JHHC. Where necessary, refinement of theses sub-population analyses was adapted from feedback received from clinical and managerial colleagues.

5 RESULTS

The following chapter describes the characteristics of the study populations, the results of the investigation of factors that underlie participation in the care management programs, the derivation and application of models to predict participation, and the measurement of patients' outcomes following participation or non-participation in care management.

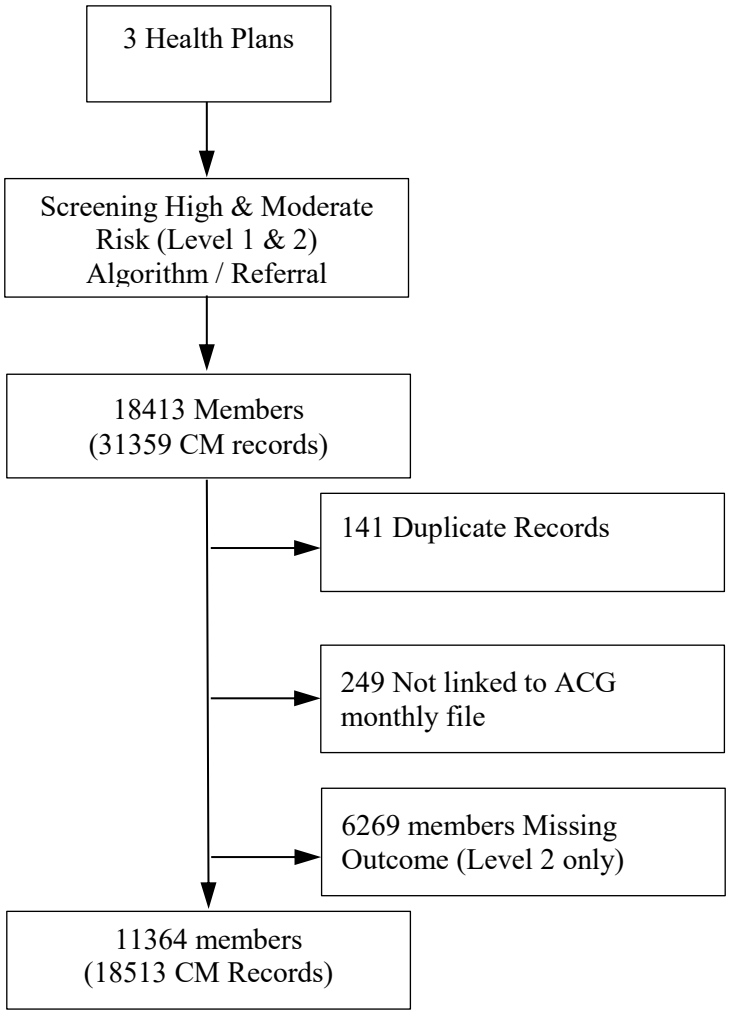
5.1 Description of Study Population

A total of 18,413 members were screened for seven care management programs by JHHC from September 1, 2009 to December 31, 2012. The members had one or multiple care management records providing 31,359 records. Members with duplicate CM records (n= 141) were deleted. The requirement that the cases could be linked to the longitudinal claims records resulted in a further loss of 249 members. After those exclusions the initial study sample consisted of 18,023 members with 29,934 separate CM records. The care management records indicate whether a member was enrolled or not ("unmanaged") in one or more care management programs.

The care management records were linked to the claims data based on the month of analysis. Specifically, from the date of a decision to enroll or not, the outcome was linked to the claims records for the immediately preceding 12 months. Where the decision of the patient to enroll or not to enroll was missing (only occurred for moderate risk, "level 2" patients) these claims records were censored from the final data set (see appendix 8.3.1 for an analysis of the missing data). Care management enrollment outcomes were present for all high risk (JHHC "Level 1") screened patients, but missing for some moderate risk (JHHC "Level 2") patients. For members

screened from the Priority Partners plan there were 5451 records without a recorded outcome, and 2871 records with an outcome. It was assumed that the members without an outcome were not followed up during the screening period, but were subsequently reentered into the screening algorithm in the succeeding month. This assumption was confirmed by the case management team. Figure 5-1 presents the consort diagram, representing the process of selecting the final study sample based of record availability. The final sample consisted of 11364 members with 18513 CM Records.

Figure 5-1: Consort Flow Diagram



5.1.1 Study population summary

Table 5-1 shows the demographic characteristics for each study member at the time of their only (or initial) case management screening (total population of 11,364). The results are presented for each of the three health plans separately.

The final study population was 64.6% female (EHP 63.7%, PP 68.8, USFHP 52.8%), with an average age of 49.9 years (EHP 50.1, PP 44.0, USFHP 68.2). They were predominantly multimorbid with a mean number of chronic conditions of 4.5 (EHP 3.4, PP 4.4, USFHP 6.2), 28.4% of the members being classified as frail (EHP 19.0, PP 31.6, USFHP 31.0). The condition across all sub-groups was: diabetes 38.4%; asthma of 36.9%; lipidemia 45.2%; hypertension 70.5%; and depression 40.2%.

Following screening, 40.2% of the members invited, enrolled in a case management program (EHP 38.3%, PP 42.5%, USFHP 35.9%) with 85.8% of this "joining" sub-group remained enrolled for at least 6 months (EHP 89.8%, PP 80.8%, USFHP 96.1%), and 67.9% for at least 12 months (EHP 76.6, PP 60.0%, USFHP 80.9%). The proportion of Medicaid plan members enrolling in care management programs appeared to be inversely related to the number of chronic conditions and Major Aggregate Diagnosis Groups (ADG), both measures of multimorbidity. Members with no chronic conditions enrolled at a rate of 58.74%, which was reduced to a rate of 33.44% for those with six chronic conditions (see Figure 5-2). Similarly, Figure 5-3 shows that patients with no Major ADGs had a care management enrolment rate of 58.53%, but this is reduced to 33.51% for patients with four Major ADGs.

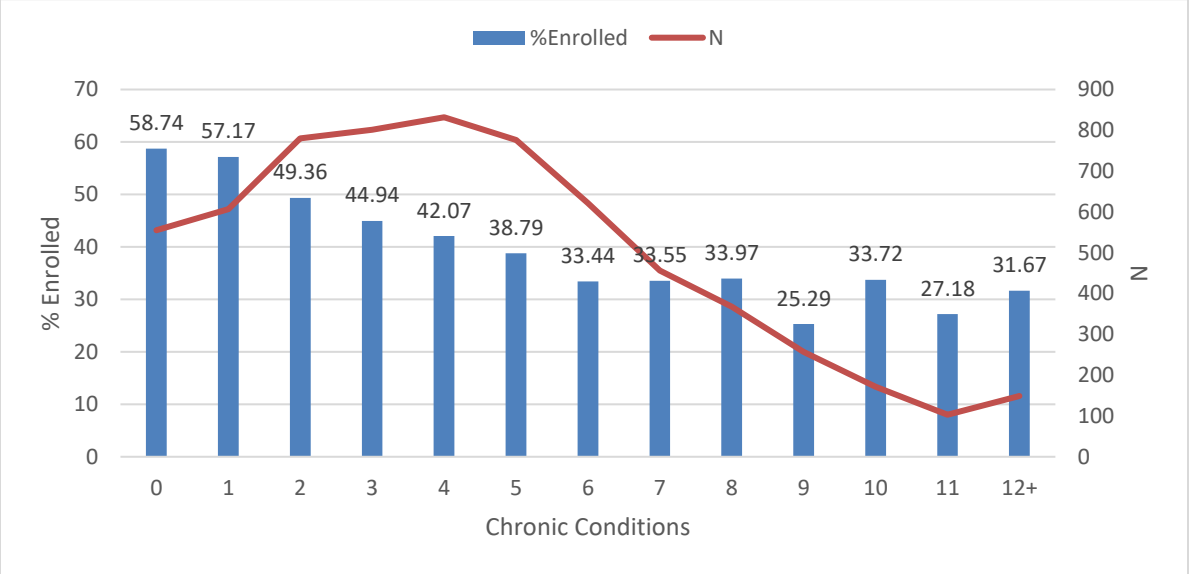
Table 5-1: Demographic Characteristics: Three Health Plans, Mean (sd)

Characteristic	*Employee Health (Commercial)*		*Priority Partners (Medicaid)*		*US Family Health (DoD)*	
N	2,836		6,478		2,050	
Female	0.6368	(0.4810)	0.6879	(0.4634)	0.5283	(0.4993)
Region						
Baltimore City	0.6227	(0.4848)	0.4555	(0.4981)	0.2195	(0.414)
Baltimore County	0.2542	(0.4355)	0.1047	(0.3061)	0.3805	(0.4856)
Eastern Shore	0.0116	(0.1073)	0.2187	(0.4134)	0.0288	(0.1672)
Southern	0.0638	(0.2445)	0.1511	(0.3582)	0.1361	(0.343)
Age at Screening	50.0846	(12.172)	43.9548	(12.218)	68.2210	(13.022)
Age 65+	0.0917	(0.2886)			0.6337	(0.4819)
Race						
Black			0.5435	(0.4981)	0.2361	(0.4248)
White			0.3692	(0.4826)	0.7195	(0.4493)
Other			0.0282	(0.1657)	0.0317	(0.1753)
Chronic Conditions	3.4115	(2.4194)	4.4461	(3.0781)	6.1580	(3.0359)
Major ADGs	1.6266	(1.4295)	2.5695	(1.7426)	2.7673	(1.5242)
Frailty	0.1904	(0.3927)	0.3163	(0.4651)	0.3102	(0.4627)
Probability IP Hospitalization	0.1384	(0.1253)	0.2683	(0.2013)	0.2986	(0.1797)
Rescaled Total cost index	5.2907	(4.5242)	8.5502	(6.4152)	4.1310	(2.5299)
Generic Drug count	10.2405	(6.2030)	14.4923	(8.8450)	14.1751	(6.9260)
Unique Provider count	4.5732	(2.7407)	4.4057	(2.9845)	5.2855	(2.7871)
Specialty count	3.7920	(2.0359)	3.4906	(2.1194)	4.2411	(2.0378)
Plan Enrollment						
Enrolled > 6mth	0.8977	(0.3030)	0.8078	(0.3941)	0.9610	(0.1937)
Enrolled > 12mth	0.7659	(0.4235)	0.5997	(0.4900)	0.8088	(0.3934)
Condition Prevalence						
Asthma	0.2486	(0.4323)	0.4392	(0.4963)	0.3176	(0.4656)
Rheumatoid Arthritis	0.0511	(0.2203)	0.0344	(0.1823)	0.0600	(0.2375)
Congestive Heart Failure	0.0811	(0.2730)	0.1425	(0.3496)	0.2234	(0.4166)
Depression	0.3078	(0.4617)	0.4560	(0.4981)	0.3610	(0.4804)
Diabetes	0.3593	(0.4799)	0.3572	(0.4792)	0.5029	(0.5001)
Lipidemia	0.4580	(0.4983)	0.3606	(0.4802)	0.7298	(0.4442)
Hypertension	0.6714	(0.4698)	0.6670	(0.4713)	0.8727	(0.3334)
Ischemic Heart Disease	0.0832	(0.2763)	0.1096	(0.3124)	0.2693	(0.4437)
Case Management Participation						
Enroll in CM program	0.3829	(0.4862)	0.4248	(0.4944)	0.3590	(0.4798)
CM Program > 12mths	0.4609	(0.4987)	0.1642	(0.3705)	0.2407	(0.4279)

Mean (standard deviation)

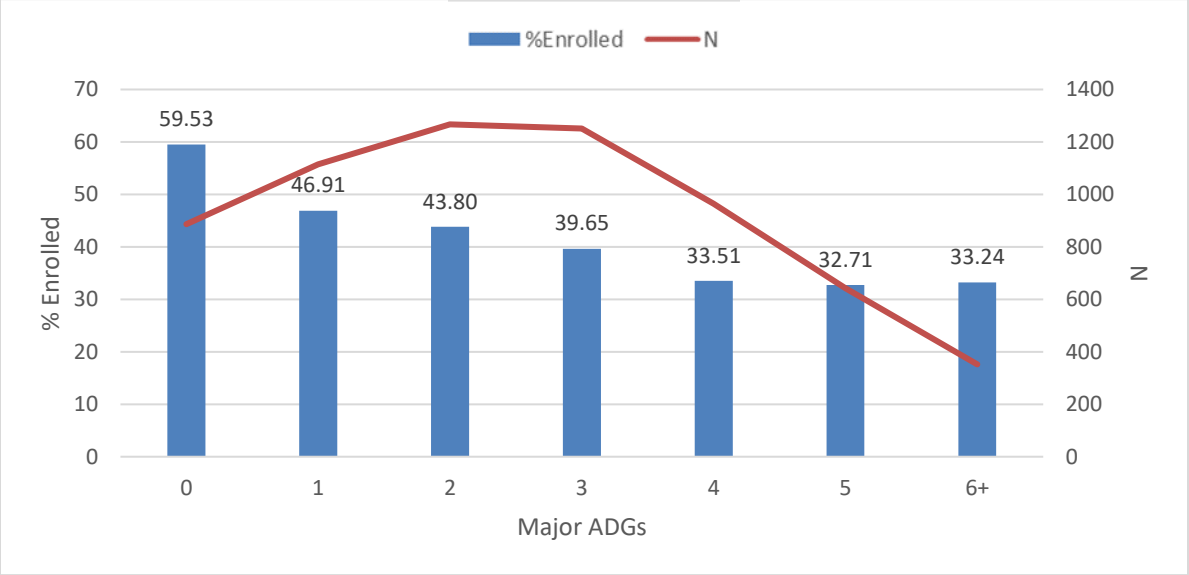
Note: for those members with two or more CM programs the results shown for first occurrence in study data.

Figure 5-2 Care Management Enrollment Rate by Chronic Condition Count: Medicaid Plan



Note: Total n across all JHHC plans = 11,364

Figure 5-3 Care Management Enrollment Rate by Major ADG: Medicaid Plan



Note: Total n across all JHHC plans = 11,364

The next three sections present analyses of factors related to CM program enrollment, separately for each health plan.

5.1.2 Medicaid Plan population: Priority Partners

Table 5-2 presents the results of the logistic regression on the care management program enrollment outcome. The data related to initial Case Management records for Priority Partners members who were screened as either high or moderate risk (level 1 or level 2).

For this Medicaid population the initial probability of a patient enrolling in a case management program after screening was 42.5%. Subsequent outcomes appeared to be conditional on the first outcome, such that the probability of a patient enrolling a second time, following an initial enrollment was 88.1%, while the probability of enrolling after initially declining to enroll was much lower at 27.2% (the odds ratios for these outcomes are shown in Table 8-2 and Table 8-3).

Statistically significant increases in enrollment were produced where the odds ratio was greater than one, i.e. a higher probability of members enrolling in a care management program than the base case. A significantly higher odds ratio occurred for black members compared to white, and whether referred or only screened via the JHHC algorithm. For black patients there was almost a 48% increase in the rate of enrollment compared with white patients (holding other variables the same), indicated by an odds ratio (OR) of 1.478 with a 95% confidence interval (CI) of 1.297 to 1.684 (OR 1.478, CI 1.297- 1.684). Other increases in enrollment were associated with members who had been referred for case management (OR 2.243, CI 1.838 - 2.737), and those with higher

numbers of specialists seen (OR 1.099, 1.031 - 1.172). These last two effect may be the result of increased activity by and with providers.

Significant reduction in care management enrollment was associated with a range of variables related to increased multimorbidity (or comorbidity), and age. Older members (aged 35-64) were 24% less likely to enroll than younger (aged 18-34) holding other variables the same (OR 0.761, CI 0.659 - 0.878). An increase in the number of chronic conditions, ADGs and generic drug count also showed reductions in care management enrollment. Up to 53% reduction in enrollment for 6 or more chronic conditions compared to none (OR 0.474, CI 0.335 - 0.671), and 65% for 4 or more major ADGs (OR 0.445, CI 0.344 - 0.576). These results would suggest that with increase in multimorbidity, a member was less likely to enroll in a case management program. Two specific conditions showed significant reductions in the rate of enrolment, rheumatoid arthritis (OR 0.717, 0.528 - 0.972) and hypertension (OR 0.786, 0.684 - 0.904).

Table 5-2 Impact of factors on member's joining (yes/no) CM program: Medicaid population

Variable	Odds Ratio Estimate	95% CL	
Gender Male vs Female	0.918	0.807	1.045
Region			
Central vs Baltimore City	0.749	0.472	1.188
County vs Baltimore City	**0.778**	**0.64**	**0.946**
Eastern Shore vs Baltimore City	0.894	0.766	1.042
Other vs Baltimore City	0.595	0.302	1.171
Southern vs Baltimore City	1.008	0.851	1.193
Western vs Baltimore City	0.849	0.644	1.119
Age 35-64 (base 18-34)	**0.761**	**0.659**	**0.878**
Race			
Black vs White	**1.478**	**1.297**	**1.684**
Other vs White	0.876	0.616	1.245

Variable	Odds Ratio Estimate	95% CL	
Unspecified vs White	1.162	0.900	1.499
Primary Care Provider Multiple vs 1	**0.605**	**0.523**	**0.7**
Risk level (vs Level 2 - Moderate)			
Level 1 - High	**2.301**	**2.002**	**2.645**
Other	**1.769**	**1.444**	**2.168**
Chronic Conditions (vs none)			
1	**0.735**	**0.543**	**0.996**
2	**0.696**	**0.511**	**0.947**
3	**0.654**	**0.476**	**0.900**
4	**0.641**	**0.461**	**0.893**
5	**0.599**	**0.424**	**0.846**
6+	**0.474**	**0.335**	**0.671**
Major ADG (vs none)			
1	**0.658**	**0.524**	**0.826**
2	**0.656**	**0.517**	**0.832**
3	**0.544**	**0.423**	**0.699**
4	**0.445**	**0.344**	**0.576**
Frailty	1.015	0.896	1.150
Referral into CM	**2.243**	**1.838**	**2.737**
Generic drug count	**0.987**	**0.978**	**0.996**
Unique Provider Count	0.976	0.934	1.020
Number of Specialties	**1.099**	**1.031**	**1.172**
No Generalist	0.785	0.601	1.027
Condition			
Asthma	0.956	0.846	1.081
Rheumatoid Arthritis	**0.717**	**0.528**	**0.972**
Congestive Heart Failure	1.003	0.846	1.190
Depression	0.914	0.807	1.035
Diabetes	0.943	0.828	1.074
Disorders of Lipid Metabolism	1.010	0.877	1.163
Hypertension	**0.786**	**0.684**	**0.904**
Ischemic Heart Disease	0.923	0.757	1.124
Enrollment in Health Plan			
6 months	0.944	0.781	1.140
12 months	1.146	0.997	1.318

Bold indicates factor significant at 95% level
Medicaid plan, Screened for Care Management High and Moderate Risk, n = 6029, probability = 0.4254
Baseline odds for a Female aged 18-34, White, Baltimore City = 0.8534
Abbreviations: CL, confidence limit

5.1.3 Effects of Region and Care Manager

To investigate whether region and the care managers exhibited a global effect distinct from the patient level effects, random effects models were used. The multi-level random effects models were tested against the null model (i.e. the base model) for significance, by comparing the ratio of likelihoods for the respective models (SAS procedure COVTEST). Table 5-3 below shows the three multi-level models; the first using region as a global effect, the second using care manager, the third model used both region and care manager. The covariance tests for the medicaid cohort, shown in Table 5-1, did not have any significant results for any of the models (respective probabilities of 0.2095, 0.1333 and 0.1825). Therefore, for the Medicaid plan data the null hypothesis of no random effects was accepted. It was therefore concluded that the region and care manager global effects were not significant and the patient level effects found above represented independent explanatory factors.

Table 5-3 Tests of Covariance Parameters Based on the Residual Pseudo-Likelihood, on Three Nested Models, Medicaid plan data

Variable	-2 Residual Log Pseudo-Likelihood	Chi Squared	Pr > ChiSq
Region	26448	0.65	0.2095
Care Manager	21862	1.23	0.1333
Region (Care Manager) *	21912	0.82	0.1825

H^o: No random effects.
P-value based on a mixture of chi-squares.
* nested model: level 1 Patient, level 2 Care Manager, level 3 Region

While the multi-level models were significant, the odds ratios showed a pattern consistent with the single level models. In Table 5-4 selected odds ratios are presented for the multi-level models (see appendices 8.3.1 for full results). These are consistent with the base model and earlier

results. The odds ratios show that younger aged patients, and patients with lower levels of multimorbidity (Major ADGs), are more likely (holding other effects the same) to enroll in a care management program than older patients and those with higher levels of multimorbidity. For younger patients the odds ratios were 1.401, 1.296 and 1.325 for the three nested models. The odds ratios for multimorbidity show a steady decline for all three models from patients with no Major ADGs (less complex) to those with four or more (most complex), with the odds ratios ranging from 1.926 to 1.223, 1.759 to 1.161 and 1.939 to 1.224 for the three models. The multi-level models all showed that there was higher enrollment amongst black patients compared to white patients, with statistically significant odds ratios of 1.347, 1.419 and 1.370.

Table 5-4 Impact of factors on member's joining (yes/no) CM program: Selective List of odds ratios from Three Nested Models for Medicaid Plan

Variable	Odds Ratio Estimate	95% CL	
Care Manager Model			
Age 18-34	1.401	1.210	1.622
Black vs White	1.347	1.186	1.530
ADG 0 v 4+	1.926	1.478	2.509
ADG 1 v 4+	1.418	1.167	1.724
ADG 2 v 4+	1.511	1.269	1.800
ADG 3 v 4+	1.223	1.033	1.448
Region Model			
Age 18-34	1.296	1.126	1.492
Black vs White	1.419	1.253	1.607
ADG 0 v 4+	1.759	1.371	2.256
ADG 1 v 4+	1.305	1.083	1.572
ADG 2 v 4+	1.321	1.120	1.558
ADG 3 v 4+	1.161	0.990	1.362
Region (Care Manager) Model*			
Age 18-34	1.325	1.137	1.544
Black vs White	1.370	1.202	1.561
ADG 0 v 4+	1.939	1.477	2.545
ADG 1 v 4+	1.438	1.174	1.761
ADG 2 v 4+	1.528	1.278	1.827
ADG 3 v 4+	1.224	1.032	1.451

95% CI, confidence interval
* nested model: level 1 Patient, level 2 Care Manager, level 3 Region
See appendices 8.3.1 for full results

5.1.4 Employee Health Plan

The results of the linear regression on the Employee Health Plan population, where the dependent variable was enrolling in the Care Management program, are presented in Table 5-5. No significant regional effects were shown, but lower enrolment was associated with members aged 65 years and older (OR 0.525, CI 0.348 - 0.791). Lower enrolment was also observed as multimorbidity increased; shown by the consistent reduction in the odds ratios as the number of chronic conditions increased and the number of major ADGs increased. A patient with two chronic conditions showed a 36% reduction in the rate of enrollment (adjusting for other factors) compared to a patient with no chronic conditions, and a patient with 4 chronic conditions showed a further reduction of almost 49%.

Significant increases in the rate of enrollment was exhibited for members with one primary care physician (compared to many), those with frailty, who had been referred, or with increased numbers of specialty physicians seen. Referral showed the highest effect with patients who were referred being more than 300% more likely to enroll adjusting for other factors (OR 3.192, CI 2.235 - 4.559). Those who were frail showed a 42% increase in enrollment (OR 1.424, 1.147 - 1.767).

Higher rates of enrollment were observed for four specific conditions, asthma (OR 1.225, CI 1.000 - 1.501), diabetes (OR 1.404, CI 1.162 - 1.697), hypertension (OR 1.554, CI 1.244 - 1.942) and ischemic heart disease (OR 1.458, CI 1.055 - 2.015).

Table 5-5 Impact of factors on member's joining (yes/no) CM program: Employee Health Plan

Variable	Odds Ratio Estimate	95% CL	
Gender M vs F	0.910	0.753	1.101
Region			
Central vs Baltimore City	1.201	0.277	5.210
County vs Baltimore City	0.979	0.804	1.192
Eastern Shore vs Baltimore City	0.920	0.420	2.019
Other vs Baltimore City	1.132	0.681	1.881
Southern vs Baltimore City	0.835	0.559	1.246
Western vs Baltimore City	0.551	0.257	1.181
Age (base 18-34)			
Age 35-64	0.984	0.752	1.287
Age 65+	**0.525**	**0.348**	**0.791**
Primary Care Provider (Base >1)			
No PCP	1.835	0.845	3.984
1 PCP	**2.305**	**1.056**	**5.029**
Chronic Conditions (vs none)			
1	0.837	0.572	1.226
2	**0.642**	**0.438**	**0.941**
3	0.746	0.501	1.112
4	**0.513**	**0.335**	**0.785**
5	**0.447**	**0.282**	**0.711**
6+	**0.407**	**0.252**	**0.658**
Major ADG (vs none)			
1	**0.626**	**0.491**	**0.798**
2	**0.536**	**0.406**	**0.707**
3	**0.497**	**0.353**	**0.700**
4	0.720	0.498	1.042
Frailty Y vs N	**1.424**	**1.147**	**1.767**
Referral into CM	**3.192**	**2.235**	**4.559**
Generic Drug Count	**0.959**	**0.940**	**0.978**
Unique Provider count	0.945	0.872	1.025
Specialty count	**1.122**	**1.008**	**1.250**
No Generalist Seen Y vs N	1.126	0.734	1.729
Condition			
Asthma	**1.225**	**1.000**	**1.501**
Rheumatoid Arthritis	0.771	0.517	1.151
Congestive Heart Failure	0.975	0.709	1.340

Variable	Odds Ratio Estimate	95% CL	
Depression	0.895	0.735	1.091
Diabetes	**1.404**	**1.162**	**1.697**
Disorders of Lipid Metabolism	0.821	0.673	1.002
Hypertension	**1.554**	**1.244**	**1.942**
Ischemic Heart Disease	**1.458**	**1.055**	**2.015**
Enrollment in Health Plan			
6 months	1.300	0.867	1.950
12 months	0.841	0.658	1.076

Bold indicates factor significant at 95% level
EHP, Screened for Care Management High and Moderate Risk,
n = 2692, probability = 0.3763
Baseline odds for a Female aged 18-34, White, Baltimore City = 0.2160
Abbreviations: CL, confidence limit

5.1.5 US Family Health Plan

The results of the linear regression on the US Family Health Plan (DoD) population, where the dependent variable was enrolling in the Care Management program are presented in Table 5-6. Unlike the other populations in the study significant effects were shown for specific regions. Three regions showed higher rates of enrollment than Baltimore City (the baseline). These were Central (OR 2.386, CI 1.228 - 4.638), Eastern Shore (OR 1.828, CI 1.012 - 3.301), and Southern (OR 1.605, CI 1.144 - 2.251).

In contrast to the Medicaid population, no significant race effect was shown (OR 1.015, CI 0.797 - 1.291). The USFHP population were also different as it showed no significant effect associated with increased morbidity (Chronic conditions or Major ADG). Referrals however showed an increased rate of enrollment over those not enrolled of 180% (OR 1.810, CI 1.355 - 2.419).

Condition specific effects were significant for only two conditions, asthma and diabetes. Similar to the Medicaid population these both had lower rates of enrollment, asthma (OR 0.624, CI 0.495 - 0.786), and diabetes (OR 0.550, CI 0.445 - 0.680).

Significant effects were also associated with the duration of enrollment in the plan. For members with at least 12 months of continuous plan enrollment prior to screening, enrollment for care management was 55% higher adjusting for other factors (OR 1.556, 1.173 - 2.064), while those with at least 6 months of continuous plan enrollment the care management enrollment was reduced (OR 0.438, CI 0.253 - 0.759).

Table 5-6 Impact of factors on member's joining (yes/no) CM program: US Family Health Plan

Variable	Odds Ratio Estimate	95% CL	
Gender Male vs Female	0.812	0.659	1.001
Region			
Central vs Baltimore City	**2.386**	**1.228**	**4.638**
County vs Baltimore City	1.25	0.954	1.638
Eastern Shore vs Baltimore City	**1.828**	**1.012**	**3.301**
Other vs Baltimore City	1.152	0.801	1.656
Southern vs Baltimore City	**1.605**	**1.144**	**2.251**
Western vs Baltimore City	1.213	0.822	1.79
Age (base 18-34)			
Age 35-64	0.98	0.476	2.018
Age 65+	0.914	0.439	1.902
Race			
Black vs White	1.015	0.797	1.291
Other vs White	0.861	0.493	1.504
Unspecified vs White	1.277	0.562	2.9
Chronic Conditions (vs none)			
1	1.378	0.445	4.266
2	1.364	0.458	4.059
3	1.891	0.637	5.613
4	1.591	0.537	4.712
5	1.415	0.474	4.223
6+	1.316	0.439	3.951
Major ADG (vs none)			
1	0.698	0.393	1.238
2	0.960	0.542	1.699
3	0.737	0.41	1.323
4	0.921	0.509	1.669
Frailty Y vs N	1.188	0.959	1.471
Referral into CM	**1.810**	**1.355**	**2.419**
Generic Drug Count	**0.980**	**0.962**	**0.999**
Unique Provider count	1.054	0.981	1.132
Specialty count	0.969	0.877	1.069
No Generalist Seen Y vs N	3.312	0.931	11.779
Condition			

Variable	Odds Ratio Estimate	95% CL	
Asthma	**0.624**	**0.495**	**0.786**
Rheumatoid Arthritis	0.702	0.458	1.074
Congestive Heart Failure	0.996	0.777	1.277
Depression	1.124	0.9	1.404
Diabetes	**0.550**	**0.445**	**0.680**
Disorders of Lipid Metabolism	0.880	0.69	1.124
Hypertension	1.106	0.799	1.532
Ischemic Heart Disease	1.228	0.961	1.567
Enrollment in Health Plan			
6 months	**0.438**	**0.253**	**0.759**
12 months	**1.556**	**1.173**	**2.064**

Bold indicates factor significant at 95% level
USFHP, Screened for Care Management High and Moderate Risk, n = 2028, probability = 0.3585
Baseline odds for a Female aged 18-34, White, Baltimore City = 0.6284Abbreviations: CL, confidence limit

5.1.6 Summary of initial analyses

These initial analyses found a number of individual level factors associated with a patient's likelihood to enroll or not to enroll in a case management program. Patients with higher multimorbidity, and older patients, holding other effects the same, were associated with a decreased propensity to enroll in care management programs.

Higher enrollment in the care management programs (holding other effects constant) was shown therefore in younger and less multimorbid patients. Higher propensity to enroll was also found in black patients compared to white patients for the Medicaid plan, while the USFHP plan did not show a significant race effect. For all plans, members who had been referred to care management by a physician or other clinicians also showed increased enrolment. Condition specific effects were found, but these varied between the three health plan sub-populations, both

with respect to which conditions showed significant enrollment effects, and also whether the condition was associated with increased or decreased enrollment rates.

In order to test if the effects found were at the patient level and might be due to higher level effects (e.g. region), multilevel models were tested on the Medicare population. The multilevel (random effects) models were created to test if there were regional and care manager global effects. These global effects were not found to be significant, and therefore patient level effects were confirmed. Furthermore, the multilevel effects models also produced results which generally confirmed those found with the original single level model. Specifically, enrolment was again found to be associated with younger patients (holding other factors constant), black patients, and those with less multimorbidity.

5.2 Patient Participation Risk Models

The following sections describe the creation of risk models to predict member enrolment in care management program following outreach. The initial approach was to create a model using existing claims data using the factors identified in the preceding sections. Further models were then created using exploratory factor analysis using additional patient survey data.

5.2.1 Models for predicting participation in case management programs

Two approaches were used to train and validate the initial models. The main approach was a split half validation, where the regression model was trained on a random sample of 50% of the data across all plans, and validated on the other 50%. An alternative method, was also examined, by training the model on the Medicaid population data and then validate on the other two plans, with variants using the other two planes. The alternative (plan based) method was found to achieve inconsistent results across the three plans, compared to the more consistent results that the split-half validation model achieved.

5.2.2 Split half validation

The entire data set was randomly assigned to one of two sub sets, such that approximately 50% of the data was assigned to each. A training data set was used to derive the model coefficients, and the second data set was used for validation. The validation results are shown in Table 5-7 for the basic comparator model (age, gender only), initial model (six variables), the final model (16 variables), and the Score model derived from the final model. This split-half model produced a

C-Statistic for the validation data of 0.6206 for the first model compared to 0.6318 on the training data. This parsimonious model had just six variables: gender, age; Major ADG count, referral, plan enrollment ≥ 6 months, and plan enrollment ≥ 12 months. The initial model compares favorably with a basic model which only used gender and age, and a C-Statistic on the validation data of 0.5729. Iterative improvements were made to the model by adding variables, performing step-wise regressions to arrive at optimized models, and consolidating dependent variables to ensure that variables were retained that formed a group, for example, retaining all Chronic Condition count variables. The final model contained 16 variables, with a C-Statistic on the validation data of 0.6327 (0.6622 on the training data). The variables with multiple values were converted in to dichotomous variables to facilitate an easier conversion in to a score, using the SAS SCORE function. The classification of semi-continuous variables in to separate dichotomous variables (such as Chronic Condition count, and Major ADG count) also allows for non-linear weighting to be applied. For example, using Major ADG as a continuous variable would have meant that each additional increase in the number of Major ADGs (holding other variables constant) would result in the same proportionate change in risk, whereas classification of the variables allowed different weightings to be derived for each separate count. The table also shows the C-Statistics for the validation data divided between the three plans. The Medicaid plan and the Employee plan had similar results of 0.6358 and 0.6442 respectively, with the Department of Defense plan slightly lower at 0.6209.

Table 5-7: Predictive Models performance, Split half validation: Random 50% training data, 50% validation data set

			Model C-Statistic			
Population / Plan	N	Outcome	Model 0	Model1	Model7	Score
Training Data	5701	0.4031	0.5729	0.6318	0.6622	0.6622
Validation Data	5663	0.4019	0.5754	0.6206	0.6327	0.6326
Medicaid Plan	3249	0.4217	0.5842	0.6389	0.6358	0.6357
Employee Plan	1390	0.3871	0.5678	0.6275	0.6442	0.6442
DoD Plan	1024	0.3594	0.5280	0.5612	0.6209	0.6206

Outcome: Patient Enrolled in Case Management program following screening
Model 0 independent variables: Gender, Age
Model 1 independent variables: Gender, Age, Major ADG count, Referral, Plan Enrollment ≥ 6 months, Plan Enrollment ≥ 12 months
Model 7 independent variables: Gender, Age, Primary Care Provider, Major ADG count (max 4), Chronic Count (max 6), Frailty, Referral, Generic Drug count, Selected Conditions

The Score model was derived from the final model, using an adapted form of the method described by Sullivan and colleagues (Sullivan et al., 2004), by dividing each estimate by a constant value representing the value of a single unit, and rounding to the nearest integer. The estimate for the variable age was chosen as this constant. The C-Statistics for the score model were similar to those of the final model as expected, with any differences attributed to the effect of rounding the model scores to integers.

The validation statistics for the final model are given from the validation data, for selected cut-points in Table . This shows that if a cut-point of 0.4 were chosen with all patients selected with a probability of 40% or more, 2794 would be chosen, resulting in Positive Predictive Value of 49.9% (half of the chosen patients would enroll in case management, true-positive cases), a sensitivity of 61.2% (proportion of all true-positives in the selection), and a specificity of 58.6% (proportion of all true-negatives in the selection).

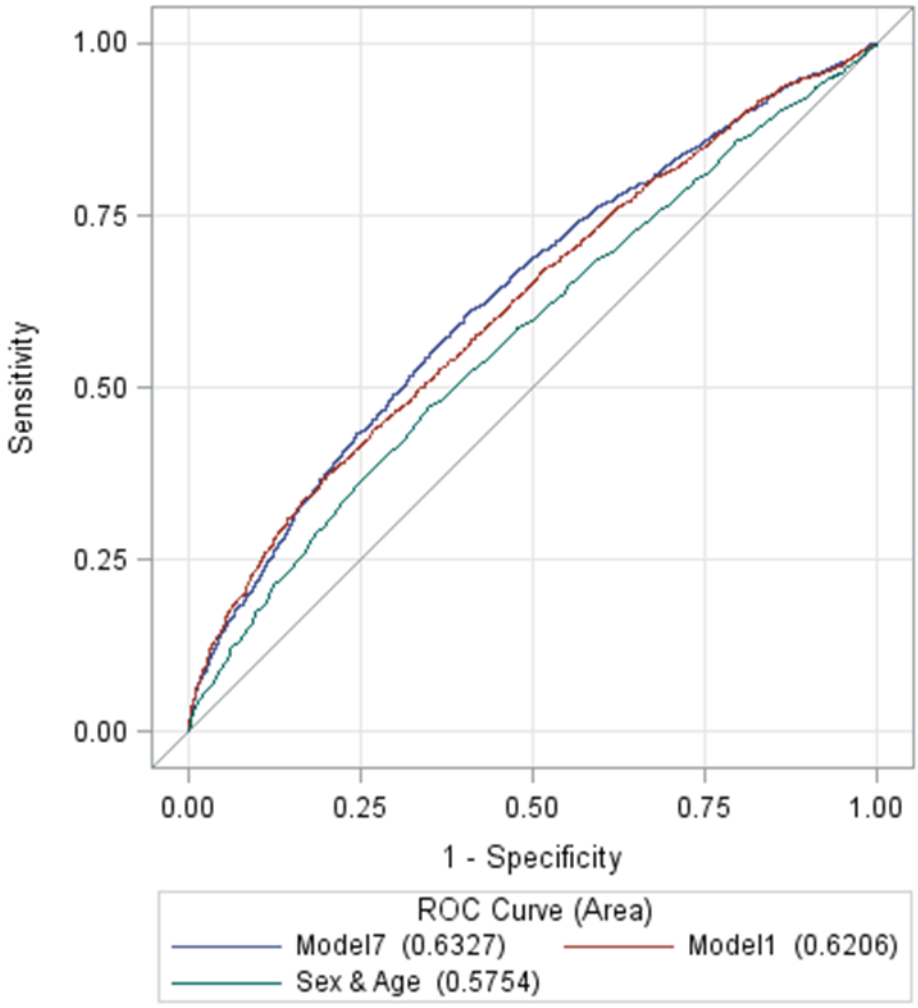
Table 5-8 Validation of predictive model: Performance for selected cut points

N	Cut Point Probability	PPV	Sensitivity	Specificity	% of Data
230	0.6	73.5	7.4	98.2	4%
1143	0.5	57.4	28.8	85.6	20%
2794	0.4	49.9	61.2	58.6	49%
4665	0.3	43.0	88.0	21.4	82%
5461	0.2	40.6	97.5	4.3	96%

Validation data, n = 5663, C-Statistic 0.6327
Dependent variable: Patient Enrolled in Case Management program following screening
independent variables: Gender, Age, Primary Care Provider, Major ADG count (max 4), Chronic Count (max 6), Frailty, Referral, Generic Drug count, Selected Conditions
PPV – Positive Predictive Value

The ROC curves for the three models are shown in Figure 5-4. This figure shows the curve of all values of Sensitivity for the models plotted against the inverse of the sensitivity. The area under each curve represents the C-Statistic, with the models with the greatest explanatory power curing towards the upper-left quadrant of the graph. The straight diagonal line represents the values achieved by a 'no better than chance' model, with all of the models lying to the left showing predictive power greater than chance.

Figure 5-4 Comparison of ROC Curves: 50% Split-half Validation data set



To facilitate an easier adoption of the model. The model was created using logit variables to easier facilitate the creation of a score. The score was calculated by dividing each variable estimate by the value of the Age at screening estimate, which was the variable chosen to be the constant denominator (the value of the weighting equal to one unit of risk for the score).

An individual's probability is calculated by summing the scores and substituting in to the following equation:

$$P_{enroll} = \frac{e^{-0.3878 + 0.0091 \times \sum score}}{1 + e^{-0.3878 + 0.0091 \times \sum score}}$$

For example, an individual aged 55 (score -55), with 1 ADG (-33), 1 chronic condition (8), who have been referred (10&), would have a total score of 27, and a resulting probability of 0.46.

$$P_{enroll} = \frac{e^{-0.3878 + 0.0091 \times 27}}{1 + e^{-0.3878 + 0.0091 \times 27}} = \frac{e^{-0.1421}}{1 + e^{-0.1421}} = \frac{0.87}{1 + 0.87} = 0.46$$

If the same patient had 4 ADGs (-45), and 6 Chronic Conditions (-40) they would have a total score of -33 and a probability of 0.33.

Table 5-9 shows the estimates and odds rations for the final model. The estimates were converted in to a score to facilitate an easier adoption of the model. The model was created using logit variables to easier facilitate the creation of a score. The score was calculated by dividing each variable estimate by the value of the Age at screening estimate, which was the variable chosen to be the constant denominator (the value of the weighting equal to one unit of risk for the score).

An individual's probability is calculated by summing the scores and substituting in to the following equation:

$$P_{enroll} = \frac{e^{-0.3878 + 0.0091 \times \sum score}}{1 + e^{-0.3878 + 0.0091 \times \sum score}}$$

For example, an individual aged 55 (score -55), with 1 ADG (-33), 1 chronic condition (8), who have been referred (10&), would have a total score of 27, and a resulting probability of 0.46.

$$P_{enroll} = \frac{e^{-0.3878 + 0.0091 \times 27}}{1 + e^{-0.3878 + 0.0091 \times 27}} = \frac{e^{-0.1421}}{1 + e^{-0.1421}} = \frac{0.87}{1 + 0.87} = 0.46$$

If the same patient had 4 ADGs (-45), and 6 Chronic Conditions (-40) they would have a total score of -33 and a probability of 0.33.

Table 5-9 Model Estimates, Odds ratio, Score

Effect	Estimate	Odds Ratio Estimate	95% CL		Score
Intercept	-0.3878				
Gender Female vs Male	0.2438	1.276	1.127	1.446	27
Age at Screening (in years)	-0.0091	0.991	0.986	0.996	-1
Primary Care Provider One v None	0.2337	1.263	1.103	1.447	26
Primary Care Provider Multiple v None	-0.2207	0.802	0.647	0.992	-24
Major ADG (vs none)					
1	-0.2991	0.741	0.603	0.911	-33
2	-0.3119	0.732	0.588	0.911	-34
3	-0.3969	0.672	0.532	0.849	-44
4	-0.4074	0.665	0.522	0.848	-45
Chronic Conditions (vs none)					
1	0.0740	1.077	0.816	1.422	8
2	-0.1606	0.852	0.645	1.125	-18
3	-0.0034	0.997	0.749	1.327	0
4	-0.1513	0.860	0.637	1.159	-17
5	-0.3968	0.672	0.489	0.924	-44
6+	-0.3630	0.696	0.505	0.958	-40
Frailty	0.2170	1.242	1.090	1.415	24
Referral	0.9739	2.648	2.170	3.252	107
Generic drug count	-0.0176	0.983	0.973	0.992	-2
Condition					
Asthma	-0.134	0.875	0.77	0.993	-15
Rheumatoid Arthritis	-0.4847	0.616	0.455	0.824	-53
Congestive Heart Failure	-0.0247	0.976	0.82	1.159	-3
Depression	-0.1350	0.874	0.769	0.992	-15
Diabetes	-0.0670	0.935	0.822	1.064	-7
Disorders of Lipid Metabolism	-0.0330	0.968	0.84	1.114	-4
Hypertension	0.1607	1.174	1.015	1.36	18
Ischemic Heart Disease	0.1734	1.189	0.986	1.433	19

Outcome: Patient Enrolled in Case Management program following screening
95% CL: 95% Confidence interval for Odds ratio
Score constant is estimate for Age at Screening (in years) = -0.0091

5.2.3 Medicaid Plan Model, Validated on Employee and US Family Health plans

An alternative method to the split-half validation approach was also created to derive and validate a model. This approach used the Medicaid data to derive a set of coefficients, which was then validated against the Employee and US Family Health plan data. Modifications using the Employee and US Family Health plan data were also tried but these yielded similar or poorer results than the Medicaid plan model. Applying the Medicaid model to the Employee plan data resulted in a high C-Statistic of 0.6410, which was almost the same C-Statistic as the originating model (0.6423) for the initial model. The US Family Health plan showed a much lower C-Statistics of 0.5443 which would indicate this model was of less significance, with a result close to 0.5 (a C-Statistic associated with random chance). The final model improved on these results with C-Statistics of 0.6410 on the Employee plan data and 0.5443 on the US Family Health plan data. The poor validation result for the US Family Health plan suggests that this model is less generalizable than the split-half model.

Table 5-10 Medicaid Plan model, Validated on Employee and US Family Health plans

			Model C-Statistic		
Population / Plan	N	Outcome	Model 0	Model1	Model7
Medicaid Plan (Training)	6478	0.4248	0.5846	0.6423	0.6654
Employee Plan (Validation)	2836	0.3829	0.5721	0.6410	0.6432
DoD Plan (Validation)	2050	0.3590	0.5244	0.5443	0.5821

Outcome: Patient Enrolled in Case Management program following screening
Model 0 independent variables: Gender, Age
Model 1 independent variables: Gender, Age, Major ADG count, Referral, Plan Enrollment ≥ 6 months, Plan Enrollment ≥ 12 months
Model 7 independent variables: Gender, Age, Primary Care Provider, Major ADG count (max 4), Chronic Count (max 6), Frailty, Referral, Generic Drug count, Selected Conditions

5.3 Factor Analysis approaches using additional patient recorded data

A factor analysis was undertaken with the SAS application (SAS Institute Inc, 2010) to review the selected items, using the approach utilized by Bower and Colleagues (Bower et al., 2002). This approach assumes that are there are unmeasured latent variables (factors) that underlie the observed variables. This method was utilized in order to explore the reduction of input variables to a measure, to inform the theoretical framework, and assess the construct validity of a measure derived from the observed variables.

A logistic regression was undertaken on the care management records for the cohort of members who completed Personal Wellness Profile (PWP) surveys and were screened for high or moderate care management. An initial model of participation in care management was formed using selected PWP variables plus age and ADGs. The PWP variables used were: general health perception, social support, last physical exam, preventive exams, and readiness to change.

A score was also created for each of the input variables using the points method described by Sullivan and Colleagues (Sullivan et al., 2004), originally developed of the Framingham Heart Study data. This tool was developed to aid calculation and decision making by clinicians.

5.3.1 Factor Analysis Updated Model using Personal Wellness Profile Data

Personal Wellness Profile data was available for those patients in the Employer plan who had carried out the survey (see appendix 8.2). Survey results were linked using the patient study identifier, for the survey that was completed prior to the first care management screening

outcome. This led to a sample of 876 patients (30.9%). Descriptive analyses were produced, followed by an exploratory factor analysis, and a further logistic regression model was produced to predict participation in a care management program using the additional PWP variables.

5.3.2 Personal Wellness Profile Factor Analysis: Adding patient engagement to predict CM enrollment

Table 5-11 shows the descriptive statistics for the Personal Wellness Profile (PWP) survey responses compared to the commercial Employee Health plan. The 877 PWP Survey responses, with an outcome, represented a 30.9% sample of all initial case management records (2836 total case management records with an associated outcome). The proportion of patients who enrolled for care management was higher for those who completed the survey than for the underlying population (45.2% compared to 38.3%). Those who completed the survey also had a lower level of chronic conditions and multimorbidity (as measured by the number of Major Aggregated Diagnoses Groups [ADG]), were younger and a higher proportion were female.

Table 5-11: Employee Health Plan Descriptive Statistics, PWP Survey

Characteristic	All Initial CM Records		PWP Survey	
	Unmanaged	Case Management	Unmanaged	Case Management
N	1750	1086	481	396
	61.7%	38.3%	54.8%	45.2%
Female	62.1%	66.3%	84.8%	84.1%
Age at Screening	51.18	48.32	48.91	46.30
Plan Enrollment (days)	672.87	664.59	708.63	682.62
Chronic Conditions	3.66	3.01	3.41	2.45
Major ADGs	1.80	1.35	1.63	0.97

PWP survey total n = 876

Table 5-12 shows the results of the factor analysis. Factors with a weighting in excess of 0.4 are highlighted to illustrated potentially correlated or grouped variables. This analysis identified five factors that appear correlated with multiple variables:

- readiness to change: exercise, nutrition, and weight;
- multimorbidity and unique provider relationship;
- readiness to change: smoking, alcohol consumption;
- preventative examinations and enrolment in the health plan;
- general health perception, support and last physical exam.

These factors appear consistent with the original reasons for selection of the items. The item *readiness to change: handle stress well* appears correlated to two factors, which may indicate that this item could be removed from the measure.

Table 5-12: Factor Analysis of selected variables: Rotated Factor Pattern

Item	Factor1	Factor2	Factor3	Factor4	Factor5
Major ADG	-0.03784	**0.80546**	0.02276	-0.06384	-0.02274
Chronic Conditions	-0.01702	**0.80604**	-0.06898	0.03881	0.05311
Unique provider	0.02112	**0.67921**	0.03388	0.15433	-0.02657
Plan Enrollment 12 months	-0.14502	-0.03675	0.14310	**0.49052**	-0.21448
General Health Perception	-0.23783	0.22995	0.07274	-0.09452	**0.59948**
Social Support	0.14961	-0.02766	-0.02708	0.21984	**0.64757**
Last Physical Exam	0.06371	-0.10964	0.02451	-0.11776	**0.58608**
Preventive Bowel	0.06284	0.14467	-0.03019	**0.63950**	-0.05216
Preventive Dental	0.27059	0.01398	-0.08623	**0.57094**	0.02822
Preventive Flu	0.10991	-0.00445	0.13038	**0.57039**	0.31122
Change Exercise	**0.81404**	-0.04596	-0.03418	0.08250	-0.04507
Change Nutrition	**0.83672**	0.02472	0.07297	0.06096	0.0451
Change Weight	**0.81146**	0.01346	0.08541	0.06158	0.04195
Change Stress	**0.63015**	-0.03525	**0.46018**	-0.00054	0.02421
Change Smoke	0.35077	0.01736	**0.81949**	0.08028	0.04060
Change Alcohol	0.35346	-0.01427	**0.83624**	0.05929	0.04566
Change Overall	**0.78659**	-0.00588	0.21281	0.02137	0.01152

* Factor loading in **bold** where > 0.4

The variables identified by the factor analysis were added to a logistic regression model on the outcome of case management participation.

Table 5-13 shows the resulting odds ratios, confidence intervals, and derived score for each variable. The scores were derived from the estimates using the points method described by Sullivan and Colleagues (Sullivan et al., 2004), originally developed from the Framingham Heart Study data. This tool was developed to aid calculation and decision making by clinicians. Each of the individual estimates was divided by the base weight (chosen to be 0.1720, the absolute value of the smallest estimate, Age 35-44) and then rounded to the nearest integer. These scores were shared with clinical colleagues for review without adjustment. The scores appear to be generally internally consistent, i.e. these progressively increase or decrease for ordinal variables. Positive scores indicated variable values that are associated with increased likelihood of participation in care management (i.e. enrolment in a care management program), while negative scores are associated with the decreased probability of a member enrolling.

The major ADG counts are significant for all values, and show odds ratios less than one, i.e. members with Major ADGs are less likely to participate than those without. The odds ratios reduce for counts of major ADGs 2, 3 and 4+ indicating that with increase morbidity members are less likely to participate. Most other variables are not statistically significant (indicated by confidence intervals that include values lower and higher than 1.0), but some individual values are significant such as age 65-69, last physical exam within one year, readiness to change stress within one month. Age 65-69 has a significant odds ratio of 0.278, indicating a 71% lower rate of participation (adjusting for other factors) than for 45-49 year old members. For members with last physical exam within one year the odds ratio was 6.589. This model produced a C-Statistic of 0.727 (compared to 0.682 without the PWP survey responses), with a Cronbach's alpha of 0.7335.

Table 5-13: CM Participation Likelihood (CMPL) Score: Based on PWP engagement response and other variables

Risk factor	Categories	Estimate	Odds Ratio	CI	Score
Intercept		1.3554			
Male		0.2631	1.301	(0.837-2.023)	2
Age					
	20-24	-0.4063	0.666	(0.209-2.209)	-2
	25-29	-0.6233	0.536	(0.257-1.111)	-4
	30-34	-0.4159	0.660	(0.337-1.286)	-2
	35-44	-0.1720	0.842	(0.498-1.42)	-1
	45-49				0
	50-54	-0.5869	0.556	(0.328-0.937)	-3
	55-59	-0.6702	0.512	(0.29-0.898)	-4
	60-64	-0.4630	0.629	(0.346-1.139)	-3
	65-69	-1.1534	0.316	(0.118-0.782)	-7
	70+	-0.9999	0.368	(0.017-2.921)	-6
Major ADG					
	1	-0.6851	0.504	(0.334-0.757)	-4
	2	-0.9108	0.402	(0.246-0.653)	-5
	3	-1.3535	0.258	(0.136-0.478)	-8
	4+	-1.5487	0.213	(0.098-0.44)	-9
Chronic Conditions					
	1	-0.1402	0.869	(0.488-1.541)	-1
	2	-0.6319	0.532	(0.295-0.949)	-4
	3	-0.5065	0.603	(0.32-1.126)	-3
	4	-0.5363	0.585	(0.303-1.12)	-3
	5	-1.0660	0.344	(0.162-0.718)	-6
	6+	-0.7026	0.495	(0.238-1.022)	-4
Frailty					
	Y	0.3228	1.381	(0.933-2.046)	2
General Health Perception					
	excellent	-1.0912	0.336	(0.052-1.782)	-6
	very good	-0.9293	0.395	(0.064-1.992)	-5
	good	-0.7703	0.463	(0.076-2.314)	-4
	fair	-1.0804	0.339	(0.055-1.735)	-6
	poor	0.2930	1.340	(0.118-17.467)	2
Social Support					
	Yes	0.6279	1.874	(0.674-5.566)	4
	No	1.0085	2.742	(0.779-10.137)	6

Risk factor	Categories	Estimate	Odds Ratio	CI	Score
Last Physical Exam					
	1 year	0.1242	1.132	(0.221-6.698)	1
	2 year	-0.3231	0.724	(0.13-4.596)	-2
	3 year	0.3692	1.447	(0.117-18.569)	2
	4 year	0.5392	1.715	(0.054-32.052)	3
	5+ year	-1.8496	0.157	(0.012-1.763)	-11
Readiness To Change:					
Change Exercise					
	no interest	1.5160	4.554	(0.738-33.708)	9
	next 6 months	1.0865	2.964	(0.528-20.248)	6
	this month	1.1010	3.007	(0.52-21.162)	6
	recently started	1.5756	4.834	(0.85-33.581)	9
	already doing this	1.3665	3.922	(0.678-27.783)	8
Change Nutrition					
	no interest	-2.4953	0.082	(0.009-0.651)	-15
	next 6 months	-1.8356	0.160	(0.02-1.077)	-11
	this month	-1.5336	0.216	(0.029-1.339)	-9
	recently started	-1.8956	0.150	(0.02-0.947)	-11
	already doing this	-1.9835	0.138	(0.018-0.884)	-12
Change Smoke					
	no interest	0.3507	1.420	(0.613-3.327)	2
	next 6 months	0.3395	1.404	(0.556-3.587)	2
	this month	0.6864	1.986	(0.625-6.435)	4
	recently started	0.7481	2.113	(0.752-6.063)	4
	already doing this	0.3267	1.386	(0.672-2.92)	2
Change Weight					
	no interest	1.9378	6.943	(1.545-35.751)	11
	next 6 months	1.6536	5.226	(1.365-23.465)	10
	this month	1.2858	3.618	(0.951-16.154)	7
	recently started	1.4572	4.294	(1.151-18.966)	8
	already doing this	1.3514	3.863	(1.018-17.206)	8
Change Stress					
	no interest	0.7526	2.123	(0.703-6.541)	4
	next 6 months	-0.0532	0.948	(0.317-2.859)	0
	this month	0.9537	2.595	(0.918-7.51)	6
	recently started	0.1970	1.218	(0.452-3.354)	1
	already doing this	0.3914	1.479	(0.556-4.026)	2
Change Alcohol					
	no interest	-0.4891	0.613	(0.255-1.457)	-3

Risk factor	Categories	Estimate	Odds Ratio	CI	Score
	next 6 months	0.0257	1.026	(0.29-3.607)	0
	this month	-0.9616	0.382	(0.09-1.547)	-6
	recently started	-0.4223	0.656	(0.234-1.79)	-2
	already doing this	-0.6370	0.529	(0.239-1.15)	-4
Change Overall					
	no interest	-1.5137	0.220	(0.054-0.857)	-9
	next 6 months	-1.4392	0.237	(0.071-0.745)	-8
	this month	-0.8580	0.424	(0.128-1.337)	-5
	recently started	-1.2898	0.275	(0.085-0.848)	-7
	already doing this	-0.8378	0.433	(0.138-1.283)	-5

Mean rate of enrolment 45.2%, Base pr Female 45-49 = 0.8346
Intercept1.3554, Score Base weight 0.1720
Probability calculation = Exp(1.3554 + 0.172.∑score) / 1 + Exp(1.3554 + 0.172.∑score)
ROC AUC = 0.7332
CI: Odds Ratio 95% confidence interval

The model produced a C-Statistic of 0.7332. At a probability level of 0.4 the sensitivity was 66.4%, sensitivity 54.5%, and the positive predictive values was 54.6%. An individual's probability is calculated by summing the scores and substituting in to the following equation:

$$P_{enroll} = \frac{e^{1.3554 + 0.172 \times \sum score}}{1 + e^{1.3554 + 0.172 \times \sum score}}$$

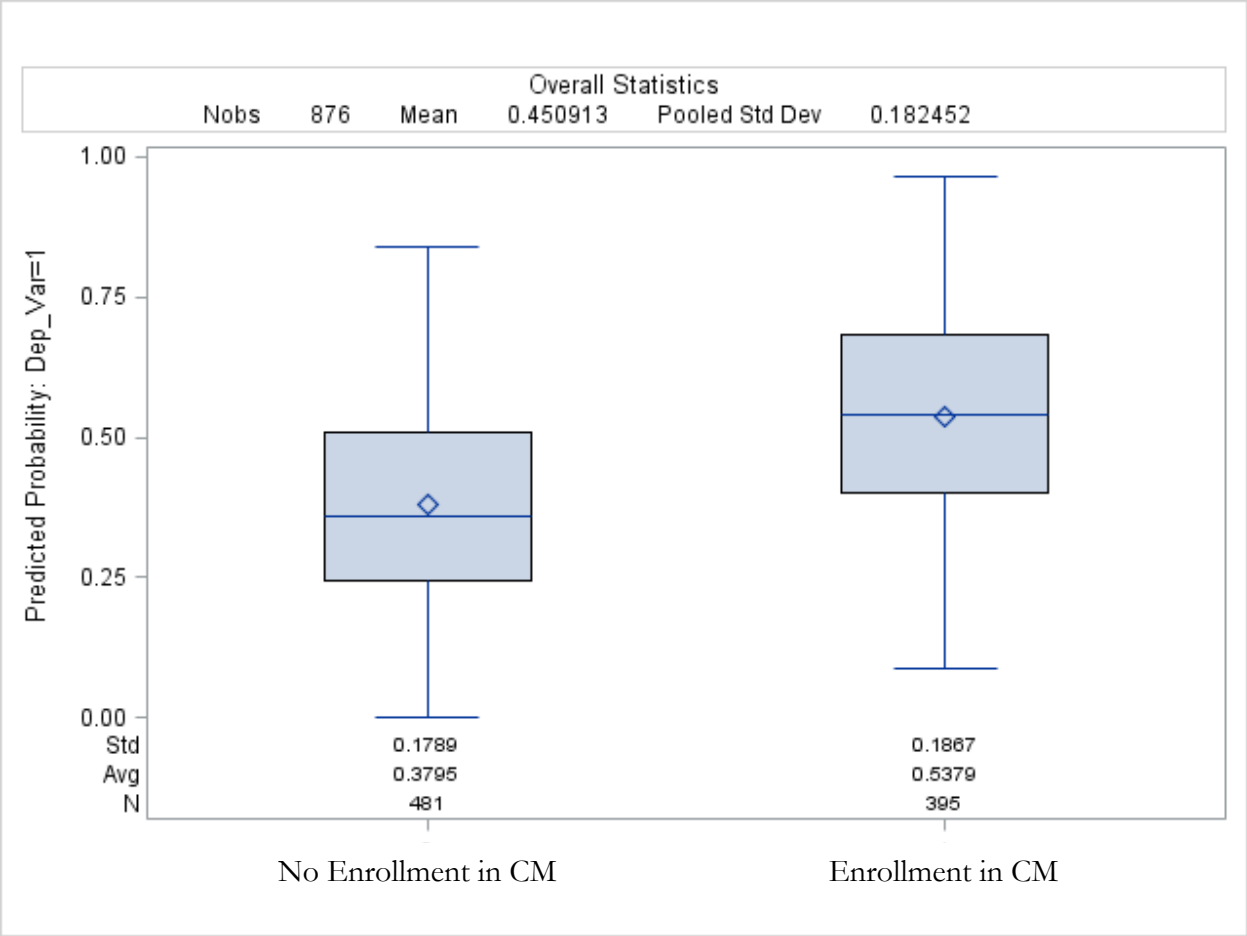
For example, an individual aged 55 (score -4), with 1 ADG (-4), 1 chronic condition (-1), poor general health perception (2), no social support (6), and no other responses, would have a total score of -1, and a resulting probability of 0.77.

$$P_{enroll} = \frac{e^{1.3554 + 0.172 \times -1}}{1 + e^{1.3554 + 0.172 \times -1}} = \frac{e^{1.1834}}{1 + e^{1.1834}} = \frac{3.26}{1 + 3.26} = 0.77$$

If the same patient had 4 ADGs (-9), and 6 Chronic Conditions (-4) they would have a total score of -9 and a probability of 0.45.

Figure 5-5 shows a box and whisker diagram of the distribution of probabilities from the initial application of the CM Participation Likelihood (CMPL) scores to the data, for those who did not enroll in the CM program (left hand distribution) and those who did enroll (right hand distribution). The non-enrollees had a mean probability of 0.3795, and the enrollees 0.5379.

Figure 5-5: Distribution of Initial CM Participation Likelihood (CMPL) Scores by Actual Enrollment



5.3.3 Principal Component Cluster Analysis

Variable Cluster Analysis using the SAS Procedure VarClus (Liau et al., 2011) was applied to the variables presented by the factor analysis to create hierarchical clusters of the variable values. This approach helped to understand the subsets of values within each variable, reducing the number of categories for consideration, with the potential for creating aggregate categories for use in sub-population analysis. An iterative approach of combining variable values from the cluster analysis led to five clusters, based on duration of patients in care management programs, plan enrolment, age, and numbers of Major ADGs and chronic diagnoses. Table 5-14 shows the results of the cluster analysis and the R-Squared value for each of the variables within its own cluster, the R-Squared values for the next nearest cluster, with the final column showing the ratio of inverse R-Squared values (1- R^2) where low ratio values are indicative of good clustering.

Table 5-14: Results of Cluster Analysis

5 Clusters	Variable	R-squared with Own	R-squared with Next	1-R^2 Ratio
Cluster 1	CM > 3 months	0.6961	0.023	0.3112
	CM > 6 months	0.8435	0.029	0.1613
	CM > 12 months	0.6454	0.023	0.3632
Cluster 2	Plan Enrollment > 12 months	0.7811	0.009	0.2210
	Plan Enrollment > 6 months	0.7811	0.064	0.2338
Cluster 3	0-2 Major ADG	0.0144	0.001	0.9874
	Age 18 - 34	0.8805	0.072	0.1287
	Age 35 - 64	0.8775	0.024	0.1256
Cluster 4	6 Major ADG	0.2039	0.002	0.7981
	0-1 Chronic Conditions	0.5085	0.067	0.5267
	Unique Providers	0.4839	0.029	0.5317
	Age 65+	0.2018	0.026	0.8198
Cluster 5	3-4 Major ADG	0.5462	0.012	0.4593
	5 Major ADG	0.5462	0.013	0.4598

The clinical variables identified by the exploratory factor and cluster analyses were combined to form four morbidity complexity groups, and sub-population analysis using these groups and other options were discussed with JHHC colleagues. These groups were used to investigate further the within-population differences in cost and utilization outcomes in section 0. These four groups were patients with:

- less than two chronic conditions;
- two or more chronic conditions with less than three Major Aggregated Diagnoses Groups;
- three or four Major Aggregated Diagnoses Groups;
- More than four Aggregated Diagnoses Groups.

5.4 Cost and Utilization Outcomes, Year 2

The costs and utilization measures 12 months following first screening (for care management) were compared across the three health plans, for those who did and did not enroll in a care management program.

These results are divided between two sub-sections, section 5.4.1 showing the overall (crude) results, and section 5.4.2 showing the results of applying propensity scoring methods. The Propensity Scoring Methods were applied to reduce the effects of selection bias and provide a comparison of outcomes based on matched pairs of those not enrolled in care management and those enrolled ("control" and "treatment" cases).

5.4.1 Cost and Utilization Outcomes, Year 2: Initial results

The tables below show a comparison of the unadjusted mean total cost, number of hospitalizations, and emergency visits per patient for the year following first screening, for those who did and did not enroll in a care management program. The Employee health plan showed an increased cost for patients who did not enroll in care management of $3,312 (23,315 - 20,003, +14.2%), while the mean number of hospitalizations and emergency visits were similar between the two sub-populations.

Table 5-15 Employee Health Plan (EHP): Year 2 Outcome Measures, Care Management Enrollment (unadjusted)

	All Data (n=2365)				
Measure	Not-Enrolled (n=1442)		Enrolled (n=923)		P value
	Mean	CI	Mean	CI	
Total Cost $	23,315	(20966-25664)	20,003	(17058-22948)	0.085
Inpatient hospitalizations	0.3454	(0.299-0.391)	0.3315	(0.276-0.387)	0.707
Emergency Visits	0.5902	(0.519-0.661)	0.5959	(0.502-0.69)	0.924

The results for the Medicaid plan also showed an increased cost for patients who did not enroll in care management of $2728 (29,373 - 26,644, +9.3%); this cost increase was statistically significant. The higher rates of inpatient hospitalizations (1.02 compared to 0.83) and emergency visits (3.13 compared to 2.63) were also statistically significantly lower.

Table 5-16 Medicaid Health Plan: Year 2 Outcome Measures, Care Management Enrollment (unadjusted)

	All Data (n=5266)				
Measure	Not-Enrolled (n=2935)		Enrolled (n=2331)		P value
	Mean	CI	Mean	CI	
Total Cost $	29,373	(27819-30926)	26,644	(24809-28479)	0.026 *
Inpatient hospitalizations	1.0273	(0.956-1.098)	0.8280	(0.751-0.905)	0.000 *
Emergency Visits	3.1322	(2.94-3.324)	2.6319	(2.461-2.803)	0.000 *

The Family Health plan in contrast to the results above, showed a decrease for patients who did not enroll in care management of $1724 (29,432-31,156, -5.9%), but the confidence intervals showed that this difference was not significant. The inpatient hospitalization rates were similar but the emergency visit rate was significantly lower for patients who did enroll in care management (0.77 compared to 0.99).

Table 5-17 Family Health Plan: Year 2 Outcome Measures, Care Management Enrollment (unadjusted)

	All Data (n=1703)				
Measure	Not-Enrolled (n=1122)		Enrolled (n=581)		P value
	Mean	CI	Mean	CI	
Total Cost $	29,432	(26900-31964)	31,156	(27265-35047)	0.466
Inpatient hospitalizations	0.6078	(0.536-0.680)	0.6489	(0.562-0.736)	0.477
Emergency Visits	0.7665	(0.671-0.862)	0.9862	(0.802-1.171)	0.038 *

To gain a greater understanding of the sub-populations of patients the groups derived from the cluster analysis were applied to the analysis.

Table 5-18 shows the outcome analysis for the 4 groups suggested by exploratory factor and cluster analysis. The first group includes all members with less than 2 chronic conditions. The other three groups include all members with 2 or more chronic conditions, and increasing number of Aggregated Diagnoses Groups (ADGs), such that the most complex group consists of members with 5 or more ADGs. A comparison of claims costs in the second year within each of these complexity groups, was made between: those who enrolled in care management, and those who did not enroll. The cost ratio is the Year 2 mean cost for those enrolled in a care management program divided by the mean cost of those who did not enroll.

Table 5-18 Mean Cost by Health Plan, Care Management Enrolled v Not Enrolled, by Count of Chronic Conditions and Major ADGs

Plan/Participation	N	Mean	(95% CI)	N	Mean	(95% CI)	Diff	P value
	Not Enrolled			CM Enrolled				
Employee Health Plan								
<2 Chronic Conditions	267	12,463	(9538-15387)	268	10,579	(8508-12649)	1,884	0.3012
0-2 Major ADGs	801	20,585	(17509-23660)	489	18,433	(15807-21058)	2,152	0.2962
3-4 Major ADGs	306	35,012	(28735-41289)	129	31,008	(20625-41390)	4,004	0.5147
5+ Major ADGs	68	45,453	(32664-58241)	37	70,643	(20288-120998)	-25,190	0.3282
Medicaid Health Plan								
<2 Chronic Conditions	367	15,104	(12193-18015)	559	13,305	(11352-15256)	1,800	0.3131
0-2 Major ADGs	921	22,844	(20399-25288)	828	20,688	(18285-23090)	2,156	0.2172
3-4 Major ADGs	1108	32,328	(29808-34846)	674	33,614	(29927-37301)	-1,287	0.5717
5+ Major ADGs	539	44,168	(39650-48684)	270	55,127	(46356-63898)	-10,959	0.0291
Family Health Plan								
<2 Chronic Conditions	42	21,592	(4786-38397)	32	16,694	(11001-22386)	4,898	0.5786
0-2 Major ADGs	499	23,318	(20388-26247)	244	23,911	(18964-28858)	-593	0.8391
3-4 Major ADGs	444	32,979	(28747-37209)	218	36,014	(28062-43965)	-3,035	0.5071
5+ Major ADGs	137	42,607	(32774-52440)	87	44,621	(36311-52930)	-2,013	0.7569

CI, Confidence Interval, CM, Care Management, Diff, Difference = Not Enrolled mean – CM Enrolled mean
Excludes patients with zero year 2 costs

The Medicaid plan had lower year 2 costs for those who enrolled for the two least complex groups of member, but the costs were higher amongst those enrolled for the two complex groups. For the employee plan those who enrolled had lower costs for all but the most complex group. The Family health plan general produced higher costs for those who enrolled, except for the least complex group. While Table 5-15 and Table 5-16 showed that the overall costs for those who enroll are generally lower in year 2 than for those who do not enroll. Creating a breakdown by complexity suggests that as the complexity increases, care management enrolment increases claims costs over those who are not enrolled. The reduced costs are for those who are less multimorbid within the population screened for care management.

5.4.2 Cost and Utilization Outcomes, year 2: Propensity Score Matching

To better adjust for potential bias when assessing the impact of CM enrollment, Propensity Score Matching (PSM) was carried out separately for each of the three plans, first using Nearest Neighbor (NN) matching and then using the Caliper method. In the NN method for each treatment case the control is chosen that had the closest propensity score (probability of enrollment in case management). This method ensures a control match for each treatment case, but does not ensure that the absolute difference in scores are close. The Caliper method allows for a minimum absolute difference in prevalence to be specified, but does result in data loss where a match cannot be found within the specified absolute difference (Coca-Perraillon, 2006).

The mean prevalence scores (probability of care management enrollment) for two Propensity Score Matching (PSM) methods are show in Table 5-19. The expectation of a successful matching algorithm would produce non-enrolled and enrolled groups with similar risks of care management enrolment. The mean prevalence scores for the Near Neighbor method were statistically significantly different for the Employee Health plan (0.4487, 0.4582) and the Medicaid Health Plan (0.4325, 0.4602) with t-test probabilities of less than 0.05 (P Values 0.080, 0.000 respectively), while the scores were close for the Family Health Plan (0.3576, 0.3578). The results of the Caliper method were closer by design, and not statistically significant for any of the three plans, but this approach also leads to loss of data where ‘close’ matches are not found in the data. Across the three plans the data loss of enrolled cases without matches was: Employee Health 6.28%, Medicaid Health Plan 13.21%, and Family Health Plan 1.20%.

Table 5-19 Mean Prevalence (probability of CM Enrollment) for two Propensity Score matching (PSM) methods

	PSM - Near Neighbor							PSM - Caliper (0.01)						
	Not-Enrolled			**Enrolled**				**Not-Enrolled**			**Enrolled**			
	n	mean	CI	n	mean	CI	P value	n	mean	CI	n	mean	CI	P value
Employee Health	923	0.4487	(0.441-0.456)	923	0.4582	(0.450-0.466)	0.080	865	0.4468	(0.439-0.455)	865	0.4469	(0.439-0.455)	0.993
Medicaid Health Plan	2331	0.4325	(0.429-0.436)	2331	0.4602	(0.456-0.465)	0.000	2023	0.4364	(0.432-0.441)	2023	0.4365	(0.432-0.441)	0.973
Family Health Plan	581	0.3576	(0.350-0.365)	581	0.3578	(0.350-0.365)	0.972	574	0.3546	(0.347-0.362)	574	0.3546	(0.348-0.362)	0.995

Caliper method, % Data Loss of enrolled cases without matches:
Employee Health 6.28%, Medicaid Health Plan 13.21%, Family Health Plan 1.20%

Analysis of Year 2 Outcomes – Matched pairs

The mean annual costs, inpatient hospitalization and emergency visit rates in the 2nd year, following screening for Care Management for each of the health plans results (using the two matching methods) are in Table 5-20. The table shows the potential overall savings for each plan that the 'treatment group' (Enrollment in CM) showed compared to the 'control group' (Not enrolled).

The Employee plan showed cost reductions of $4486.86 (18.3%) using Near Neighbor matching and 4186.91 (17.1%) for Caliper matching, which were higher than the non-matched results in the previous section. The inpatient hospitalization and emergency visit rates were also reduced. The Medicaid plan showed a reduction of costs of $4074.07 (13.3%) and $1372.66 (4.6%), again with reduced hospitalization and emergency visit rates. The Family Health plan also showed cost reductions for those enrolled in care management of $2458.51 (7.3%) and $2604.29 (7.7%), which contrasts with the result in the previous section before matching was applied (costing increase of $1724.32, 5.9%).

respectively.

Table 5-20 Employee Health Plan: Propensity Score matching, Year 2 Outcome Measures, Care Management Enrollment

Plan / Measure	mean	CI	mean	CI	P value*	mean	CI	mean	CI	P value*
	Not-Enrolled		**Enrolled**			**Not-Enrolled**		**Enrolled**		
	PSM - Near Neighbor (n=1846)					PSM - Caliper (n=1730)				
	(n=923)		(n=923)			(n=865)		(n=865)		
Employee Health										
Total Cost $	24,490	(21299-27680)	20,003	(17058-22948)	0.043	24,449	(21084-27814)	20,262	(17134-23390)	0.074
Inpatient hospitalizations	0.3499	(0.292-0.408)	0.3315	(0.276-0.387)	0.654	0.3387	(0.279-0.399)	0.3329	(0.275-0.391)	0.892
Emergency Visits	0.6652	(0.565-0.765)	0.5959	(0.502-0.69)	0.322	0.6763	(0.571-0.782)	0.5977	(0.498-0.697)	0.287
Measure	Not-Enrolled		Enrolled			Not-Enrolled		Enrolled		
	PSM - Near Neighbor (n=4662)					PSM - Caliper (n=4046)				
	(n=2331)		(n=2331)		P value*	(n=2023)		(n=2023)		
Medicaid Health Plan										
Total Cost $	30,718	(28906-32531)	26,644	(24809-28479)	0.002	29,727	(27841-31613)	28,354	(26306-30403)	0.334
Inpatient hospitalization	1.0854	(1.003-1.167)	0.828	(0.751-0.905)	0.000	1.0400	(0.953-1.127)	0.8883	(0.802-0.974)	0.015
Emergency Visits	3.2986	(3.071-3.526)	2.6319	(2.461-2.803)	0.000	3.2012	(2.963-3.439)	2.695	(2.505-2.885)	0.001
Measure	Not-Enrolled		Enrolled			Not-Enrolled		Enrolled		
	PSM - Near Neighbor (n=1162)					PSM - Caliper (n=1148)				
	(n=581)		(n=581)		P value*	(n=574)		(n=574)		P value*
Family Health Plan										
Total Cost $	33,614	(29786-37443)	31,156	(27265-35047)	0.377	33,920	(30052-37788)	31,316	(27382-35251)	0.354
Inpatient hospitalization	0.6936	(0.595-0.793)	0.6489	(0.562-0.736)	0.505	0.6986	(0.599-0.799)	0.6516	(0.564-0.740)	0.488
Emergency Visits	0.8985	(0.745-1.052)	0.9862	(0.802-1.171)	0.473	0.9007	(0.745-1.056)	0.9895	(0.803-1.176)	0.472

Caliper method, % Data Loss of enrolled cases without matches:
Employee Health 6.28%, Medicaid Health Plan 13.21%, Family Health Plan 1.20%

Analysis of Year 2 Outcomes – Matched pairs by plan and sub group

The analysis of mean total cost by plan and by sub group is shown in Table 5-21. For all of the plans, and all sub groups except the highest complexity group (5+ Major ADGs) there are lower costs for the enrolled populations. The reductions in costs for the enrolled populations are consistently lower for both of the matched pairs methods. In contrast, enrolled patients in high complexity sub-groups showed a reduction compared with the all data (crude) results.

The EHP population using the PSM methods produced apparent cost savings across the three less complex sub-groups for those who enrolled in case management. The least complex group of patients with less than 2 chronic conditions showed reduced costs using the Nearest Neighbor method of $3484.61 ($10,579 for enrollees compared to 14,064 for non-enrollees, 24.8%), and $2395.36 ($10,952 - $13,347, 18.9%) using the Caliper method. The sub-group of patients with 0 to 2 Major ADGs and 2 or more chronic conditions showed cost reductions of $4192.58 (18.5%) and $4489.28 (20.0%) for the two PSM methods respectively. The third sub-group of patients with 3 or 4 Major ADGs also showed a mean cost reduction of $8350.29 (21.2%) and $8315.93 (21.1%). The highest complexity sub-group, of patient with 5 or more Major ADGs, was the only group that showed a cost increase for those enrolled in case management compared to those who were not enrolled; a mean increase of $21,898.95 (44.9%) and $18,463.00 (35.4%) using the Nearest Neighbor and Caliper methods respectively.

The Medicaid plan population showed similar results to the EHP population with the 3 least complex sub-groups showing costs savings for the enrolled population, with only the highest complexity sub-group showing an increase in cost for those enrolled in care management

compared to those who were not enrolled. The least complex group of patients with less than 2 Chronic Conditions showed reduced costs using the Nearest Neighbor method of $1634.77 (13,305-14,939, 10.9%) compared to $1480.85 (13,737-15,218, 9.7%) using the Caliper method. The sub-group of patients with 0 to 2 Major ADGs and 2 or more chronic conditions showed cost reductions of $4019.44 (16.3%) and $3468.01 (14.1%) for the two PSM methods respectively. The third sub-group of patients with 3 or 4 Major ADGs also showed a mean cost reduction of $1017.33 (2.9%) and 1274.02 (13.7%). The highest complexity sub-group, of patients with 5 or more Major ADGs, was the only group that showed a cost increase for case management enrollees compared to non-enrollees, a mean increase of $8348.21 (17.8%) and $11,288.15 (25.7%) using the Nearest Neighbor and Caliper methods respectively.

The USFHP population showed similar results to the other two populations, with only the most complex sub-group showing a cost increase for those enrolled in case management. The least complex group of patients with less than 2 chronic conditions showed reduced costs using the Nearest Neighbor method of $5902.42 (26.1%) and $10,070.68 (27.4%) using the Caliper method, but the lower number of patients in this group may underlie the large difference between the two methods. The sub-group of patients with 0 to 2 Major ADGs and 2 or more chronic conditions showed cost reductions of $4848.17 (16.9%) and $4861.80 (16.8%) for the two PSM methods respectively. The third sub-group of patients with 3 or 4 Major ADGs also showed a mean cost reduction of $1727.65 (4.6%) and $1727.65 (4.6%). The highest complexity sub-group, of patients with 5 or more Major ADGs, was the only group that showed a cost increase for those enrolled in case management compared to those who were not; a mean increase of

$1451.33 (3.4%) higher and $1451.33 (3.4%) using the Nearest Neighbor and Caliper methods respectively.

This chapter described the study populations, the results of the investigation of factors that underlie participation in the care management programs, the derivation and application of models to predict participation, and the measurement of patients' outcomes following participation or non-participation in care management.

The following chapter discusses these results, draws conclusions including potential implications for care management, and outlines the limitations of the study.

Table 5-21 Propensity Score matching, Year 2 Total Cost, Care Management Enrollment by Plan Sub-Group

Plan/Sub-Group	N	Total Cost (CI)		N	Total Cost (CI)		P value*	N	Total Cost (CI)		N	Total Cost (CI)		P value*
	Not-Enrolled			**Enrolled**				**Not-Enrolled**			**Enrolled**			
	PSM - Near Neighbor (n=1846)							PSM - Caliper (n=1730)						
Employee Health														
<2 Chronic Conditions	207	14,064	(10354-17774)	268	10,579	(8508-12650)	0.107	194	13,347	(9653-17042)	237	10,952	(8634-13270)	0.279
0-2 Major ADGs	528	22,625	(18404-26847)	489	18,433	(15807-21058)	0.098	491	22,492	(18000-26984)	462	18,003	(15264-20741)	0.094
3-4 Major ADGs	151	39,359	(29010-49707)	129	31,008	(20626-41391)	0.261	146	39,324	(28665-49983)	129	31,008	(20626-41391)	0.270
5+ Major ADGs	37	48,744	(30074-67415)	37	70,643	(20288-120998)	0.411	34	52,180	(32275-72085)	37	70,643	(20288-120998)	0.491
	PSM - Near Neighbor (n=4662)							PSM - Caliper (n=4046)						
Medicaid Health Plan														
<2 Chronic Conditions	342	14,939	(11901-17978)	559	13,305	(11353-15257)	0.374	316	15,218	(11978-18458)	382	13,737	(11476-15998)	0.461
0-2 Major ADGs	751	24,708	(21778-27638)	828	20,688	(18286-23091)	0.037	689	24,541	(21440-27642)	703	21,073	(18416-23731)	0.096
3-4 Major ADGs	821	34,632	(31606-37658)	674	33,614	(29927-37302)	0.675	689	34,829	(31522-38135)	668	33,555	(29842-37267)	0.615
5+ Major ADGs	417	46,779	(41448-52110)	270	55,127	(46356-63899)	0.110	329	43,839	(38418-49260)	270	55,127	(46356-63899)	0.032
	PSM - Near Neighbor (n=1162)							PSM - Caliper (n=1148)						
Family Health Plan														
<2 Chronic Conditions	24	22,597	(-5237-50430)	32	16,694	(11002-22387)	0.669	19	26,907	(-8685-62499)	30	16,836	(10872-22800)	0.561
0-2 Major ADGs	270	28,759	(23871-33647)	244	23,911	(18964-28858)	0.170	268	28,867	(23946-33789)	239	24,005	(18965-29046)	0.175
3-4 Major ADGs	215	37,742	(31538-43945)	218	36,014	(28062-43966)	0.736	215	37,742	(31538-43945)	218	36,014	(28062-43966)	0.736
5+ Major ADGs	72	43,169	(29016-57323)	87	44,621	(36311-52930)	0.860	72	43,169	(29016-57323)	87	44,621	(36311-52930)	0.860

6 DISCUSSION AND CONCLUSIONS

This chapter discusses the study's findings in a broader context. It will provide an overview and summary, describe potential implications for care management and future research, and will discuss limitations.

6.1 Overview

This study provides an exploration of participation (specifically enrollment) in care management plans using routine claims data and additional care management administrative data, by applying single and multilevel logistic regression techniques. Consistent with its four main aims this study: 1) developed an approach for defining and measuring the achievement of patient participation in the care management context; 2) applied a definition of participation to three different populations screened for care management, to determine which individual and organizational factors were associated with patients' participation; 3) developed models to predict participation; and 4) created an analytic approach for the measurement of care management participation across the study populations to enhance understanding of patient groups and sub-populations.

Specifically, the results identified patient factors associated with propensity to participate, further developed models to predict future participation, and further developed analytics to assist in evaluating utilization outcomes of care management programs.

6.2 Summary and Interpretation of Findings

6.2.1 Measuring patient participation

This study derived an operational definition of patient participation from routine administrative data. Specifically, patients who had been screened for care management, and then consented to enroll into a program or declined to be enrolled. This measure was achieved by linking a care management administrative database to claims data. This measure benefits from being simple to apply using routine data, and can reasonably be assumed to be consistent with self-efficacy and the evidence linking initiating change to continuing behavioral change, i.e. assuming that enrolling or initiating care management will lead to participation (Rimer, 2008).

Duration in a care management program was also analyzed, but following review with clinical and administrative colleagues, the precise reason for discontinuing enrollment could not be distinguished, so the measure was not fully developed as a dependent variable. In the future it would be useful to record the type of care management intervention, whether the patient or the plan had dis-enrolled, and the extent to which the intervention had been completed.

6.2.2 Factors Associated with Care Management participation

The initial exploratory models included a number of individual level factors associated with a patient's likelihood to enroll or not to enroll in a case management program. Patients with higher multimorbidity, and older patients, holding other effects the same, were associated with a decreased propensity to enroll in care management programs. Table 6-1 shows the odds ratios

decreasing as the number of chronic diseases increases for the Medicaid and Employee Health plans, and the odds ratios also decreasing as the number of Major ADGs increases.

Table 6-1 Patient factors with reduced likelihood of member's acceptance to join CM program: Three Health Plans

	Odds Ratio Estimates		
Variable	*Medicaid (n = 6029)*	*Employee (n = 2692)*	*US Family (n = 2028)*
Age 35-64 (base 18-34)	0.761*	0.984	0.980
Age 64+	*n/a*	0.525*	0.914
Primary Care Provider Multiple vs 1	0.605*	0.434*	*n/a*
Chronic Conditions (vs none)			
1	0.735*	0.837	1.378
2	0.696*	0.642*	1.364
3	0.654*	0.746	1.891
4	0.641*	0.513*	1.591
5	0.599*	0.447*	1.415
6+	0.474*	0.407*	1.316
Major ADG (vs none)			
1	0.658*	0.626*	0.698
2	0.656*	0.536*	0.960
3	0.544*	0.497*	0.737
4	0.445*	0.720	0.921

* significant at 95% confidence level

Selected results from tables 5-2, 5-5, 5-6

Higher enrollment in the care management programs (holding other effects constant) was shown therefore in younger and less multimorbid patients. Higher propensity to enroll was also found in black patients compared to white patients for the Medicaid plan, while the USFHP plan did not show a significant race effect. An Oregon study found no statistically significant differences in the trajectories of patients once enrolled in case management across different ethnicities differences (Quinones, Ramsey, Newsom, & Dorr, 2014), while a randomized control study that

provided culturally tailored care management interventions to black patients with diabetes did show a reduction in emergency department visits (Gary et al., 2004). The effect measured in black Medicaid patients were not likely due to the patients being younger and less multimorbid, given that these variables were included in the models and the results for the race variable were consistently significant across both patient and multi-level results, this would provide evidence of a genuine effect.

Table 6-2 Patient factors with increased likelihood of member's acceptance to join CM program: Three Health Plans

	Odds Ratio Estimates		
Variable	*Medicaid (n = 6029)*	*Employee (n = 2692)*	*US Family (n = 2028)*
Age 18-34 v 35-64	1.239*[a]	1.475[b]	1.094
Race			
Black vs White	1.478*	*n/a*	1.015
Referral	2.243*	3.192*	1.810*
Number of Specialties	1.099*	1.122*	0.969

* significant at 95% confidence level, [a] Baseline Age 35-64, [b] Age 65+
Selected results from tables 5-2, 5-5, 5-6

For all plans, members who had been referred to care management by a physician or other clinicians also showed increased enrolment. The referral of a patient to care management may be a result of increased support and encouragement a patient's provider, or there may be underlying factors not measured in the claims data. Studies have concluded that the identification and participation of high risk patients for care management can be supported by a combination of referral by a patient's primary care provider diagnoses based and predictive model screening (Cohen, Flaks-Manov, Low, Balicer, & Shadmi, 2015; Freund et al., 2011).

Condition specific effects were found, but these varied between the three health plan sub-populations, both with respect to which conditions showed significant enrollment effects, and also whether the condition was associated with increased or decreased enrollment rates. These effects may be related to the screening processes of patients, a potential confounder, rather than a direct effect on enrolment. There could also be interaction between these specific conditions and the other general morbidity effects, such as those associated with a patient having a chronic or multiple chronic diseases.

In order to test if the effects found were at the patient level and might be due to higher level effects (e.g. region), multilevel models were tested on the Medicare population. The multilevel (random effects) models were created to test if there were regional and care manager global effects. These global effects were not found to be significant, and therefore patient level effects were confirmed. Furthermore, the multilevel effects models also produced results which generally confirmed those found with the original single level model. Specifically, enrolment was again found to be associated with younger patients (holding other factors constant), black patients, and those with less multimorbidity. The confirmation of these patient level effects may need to be considered in the design of future care management screening programs, to ensure that patients are approached to enroll with appropriate recognition of their likelihood of enrolment. Understanding why these factors appear to affect enrolment emphasizes the need to acknowledge that casemix differences are assessed when designing, implementing and evaluating care management programs and their outcomes.

6.2.3 Predicting patient participation

Two types of models were explored. The first used claims and enrollment data variables that had been found to be associated with participation, and then applied the resulting odds ratios for each variable to produce a patient level probability of participation. The second type of model used additional patient reported variables from the Personal Wellness profile, and created a Care Management Participation Likelihood (CMPL) score based on each of the available consumer reported and administrative variables. The advantage of the first model type is its immediate ability to be applied to any routine claims data. The latter model offered more in depth patient beliefs and attitudes. Either predictive score could be applied (after further testing and replication) to help guide the care management outreach and enrollment process.

Adding the personal wellness profile variables did add additional explanatory power to the participation model, but given the low level of completeness of this profile, further expansion of data collection would likely be needed for this expanded score to be feasible.

For this Medicaid population the initial probability of a patient enrolling in a case management program after screening was 42.5%. Subsequent outcomes appeared to be conditional on the first outcome, such that the probability of a patient enrolling a second time, following an initial enrollment, was 88.1%, while the probability of enrolling after initially declining to enroll was much lower at 27.2%. This finding is important in understanding why those who have enrolled historically are likely to re-enroll in the future, while those who have declined historically are most likely to continue to decline enrollment.

6.2.4 Cost and Utilization outcomes

As noted in section 6.2.1 there is a need to recognize that there are potential differences in case management enrollment populations by type of morbidity. This could produce selection bias that could both positively and negatively affect any comparisons of outcomes. Firstly, a crude comparison was made of selected output between care management enrolled and non-enrolled patients across the three plans. Secondly, a comparison was made using paired matching (using PSM) of enrolled and non-enrolled patients. Finally, using four sub-population groups (discussed in the following section), a breakdown of the results by patient morbidity complexity was made to provide a differential analysis of outcomes.

The analyses compared "outcomes" of those enrolled in care management to those not enrolled, using second year (12 months after screening) utilization measures, mean total cost, hospitalizations, and emergency visits.

The unadjusted comparison across the three plans showed higher costs for those not enrolling in care management. For the Employee health plan, the mean costs were $3,312 (23,315 - 20,003, +14.2%) higher, and for the Medicaid plan the figure was $2728 (29,373 - 26,644, +9.3%). The utilization of hospital admissions and emergency visits were similar for the Employee plan between the two sub-populations, while Medicare care management non-enrolled patients had higher rates of admissions and visits. The Family Health plan had contrasting results to the other two plans, with reduced costs for those enrolled in care management of $1724 (29,432-31,156, -5.9%), but these were not statistically significant. The differences in these crude outcome statistics may have been due to the differing patient factors for the Family Health plan

recognized in the initial analysis, but confounding was also a consideration. This concern regarding potential confounders led to the enhanced analysis using matched pairs methods.

Two Propensity Score matching (PSM) methods were used, to help ensure that all patients enrolled in care management programs (the "treatment" group) had a matched pair who had not enrolled ("control") based on having as close as possible risk of participation. Despite the differences in the two methods applied (Nearest neighbor and Caliper), the results were broadly similar providing confidence in the overall direction of the cost reductions shown. After applying the PSM methods the Employee plan showed cost reductions for those enrolled in care management of $4486.86 (18.3%) and $4186.91 (17.1%), respectively for Nearest Neighbor and Caliper matching, this was higher than the non-matched. The Medicaid plan PSM results showed reduced costs of $4074.07 (13.3%) and $1372.66 (4.6%), and the Family Health plan also showed cost reductions for those enrolled in care management of $2458.51 (7.3%) and $2604.29 (7.7%). These results were similar to those in a previous study that showed savings from disease management plans (Grossmeier et al., 2013), where the Employee and Medicaid health plans both showed a decreased adjusted cost for patients who enrolled in care management of $4233 ($352.75 per month). Costs savings in a Medicaid care management program had been attributed to reduced hospitalization and specialist visit costs (Picariello, Hanson, Futterman, Hill, & Anselm, 2008).

The PSM results suggested that inpatient hospitalization and emergency visit rates were reduced for care management enrollees in the Medicaid population, but the other two plans did not show significant changes. This may indicate that the cost savings were not necessarily realized through

systematic reduction in patient utilization and claims. An Illinois Medicaid case management program showed costs savings, with lower inpatient admissions, outpatient visits, and improved quality (Phillips, Han, Petterson, Makaroff, & Liaw, 2014). Mixed results for case management were found in the review conducted by Stokes and colleagues (Stokes et al., 2015) where no significant difference in costs were found across 36 studies, but concluded that case management delivered by multi-disciplinary teams may increase effectiveness.

The use of propensity score matching demonstrated the need to apply comparative methods to reduce risk of confounding caused by selection bias. Although the crude analysis had shown cost reductions for two of the populations, the adjusted analysis demonstrated potential savings for all three plans. To gain a better understanding of the differences within the plan populations, further analysis was carried out using four sub-population groups defined by type of morbidity.

6.2.5 Sub population analysis

Four morbidity complexity groups were formed from the exploratory factor and clustering analyses. These groups were used to investigate further the within-population differences in cost and utilization outcomes. These four groups were comprised of patients with:

- less than two chronic conditions;
- two or more chronic conditions but with less than three Major Aggregated Diagnoses Groups (ADG);
- three or four Major ADG;
- More than four ADG.

These four groups made up respectively 16.4%, 40.5%, 30.8% and 12.2% of the patients in the outcomes analyses, and made up 8.2%, 32.3%, 38.0% and 21.5% of the total costs in the second year. Overall the lower costs for care management enrolled patients compared to the non-enrolled, summarized in the previous section, held for each of the sub-groups except the fourth most complex group. The reductions in costs for the enrolled populations were consistently lower for both of the matched pairs methods. While matched paired methods still showed higher costs for enrolled patients for the high complexity sub-group, the differences in costs were reduced compared with the all data (crude) results. Overall is was observed that as the complexity of the sub-groups increases, care management enrolment increases claims costs over those who are not enrolled. The reduced costs are for those who are less multimorbid within the population screened for care management. The larger difference in costs between patients with lower risk, compared to higher risk patients where the difference narrowed, had been previously reported by Sylvia and colleagues in a quasi-experimental study that selected a sample of patients who received usual care and patients who received Guided Care (Sylvia et al., 2008).

While overall these results show favorable outcomes for patients who participate in care management, they may highlight a need to review the most complex patients in the care management programs. This would be in order to understand whether their increased costs are a direct consequence of providing case management and identifying needs for care that would otherwise be reduced or ignored for patients who chose not to enroll in care management, or if other factors not available in routine claims data are relevant. Coupled with the initial finding

that participation in care management reduces with increased multimorbidity, this represents an important consideration in future care management program design.

6.3 Discussion

6.3.1 Available Data Limitations and the Future

While the study had a wide range of data available for the analysis, there were certain data related limitations. For example, only a limited exploration of enriched data, such as the Personal Wellness Profile, showed that the use of specific patient reported factors could add additional value to understand care management engagement. The factor analysis in section 5.3 produced five factors from the data, three of which cover constructs not available in the claims data: readiness to change exercise, nutrition and weight; readiness to reduce smoking and alcohol; health perception and social support. The other factors can largely be derived from current claims data, such as measures of multimorbidity, and whether preventative examinations have been undertaken. This latter factor does however highlight the importance of having longitudinal linked population health records, so that history of preventative examinations and procedures can be associated with current patient activities, particularly when these items were linked with continuous health plan enrolment (continuous plan enrollment of at least 12 month). Claims data is a good predictor of the need for case management, and is also powerful due to its availability at the time of screening, while other health risk data may not be available (Drozda, Libby, Keiserman, & Rundhaug, 2008)

The potential of Electronic Medical Record (EMR) data could not be explored within the scope of this study. However there does exist a huge potential for other constructs associated with participation and patient engagement to be explored. The claims data did not allow for the specific nature of the care management intervention to be identified, and there was therefore no ability to delineate activity associated with the normal process of care and that attributed to the care management process.

6.3.2 Patient Factors in Engagement in Care Management

A troubling finding in this study is that high morbidity burden is associated with lower likelihood of care management enrollment. Some explanations are that those patients currently receiving high levels of healthcare for their conditions may be content with current support, feel overwhelmed by the introduction of an additional care process, or may have lowered capacity to make the decision to take advantage of this likely beneficial service. The concept of a "Mental Bandwidth" has been postulated for people with multiple medical and socioeconomic challenges. This effect may be a contributing factor for members not enrolling or continuing their enrolment in case management from the Medicaid plans (Mani, Mullainathan, Shafir, & Zhao, 2013; Novotney, 2014). By extension, this effect may also inhibit individuals in effective self-management and making decisions in support of their wellbeing.

Lack of "Bandwidth" may explain why patients with high multimorbidity are less likely to enroll more generally than just those in poverty. With multiple medical conditions, high utilization of healthcare resources, multiple interactions with many health care professionals, the addition of

another consideration, i.e. care management, may be too much for an individual to be able to contemplate. Alternatively, the patient may also feel that they have sufficient healthcare support and the addition of care manager is unnecessary.

6.3.3 Implications for Care Management Plans

As noted, this study suggests that as multimorbidity increased, individuals were less likely to enroll in care management. Provided that care management is effective for these populations both in terms of improved quality and efficiency, this finding would suggest that approaches to care management programs may need to be modified to be more attractive to these very high morbidity individuals, for who these programs were specifically designed. Potential changes could include increased flexibility in approach, attention to tailored care plans, and closer coordination with the patient's PCP and current team of physicians, lead physicians or other clinical professionals. The finding that enrollment was higher among those who were referred suggests including the patient's physicians from the start provide encouragement and support for individuals. This may also indicate that certain outcomes that make a significant difference in engagement are attributable to the participation of physicians rather than the efficacy of the patients per se, and future studies should test if active physician participation contributes in care management programs to long-term patient self-efficacy. Finding that those patients who have enrolled historically are likely to re-enroll in the future, while those who have declined historically are most likely to continue to decline enrollment, presents further challenges to future studies to understand the underlying reasons for individuals to decline enrollment, and

whether there is the ability to adapt care managements programs, or the approaches to patients, to improve participation and enrollment.

Hong and colleagues in reviewing the success factors for care management programs highlighted that the need to ensure programs were customizable and adapted to local factors (Hong et al., 2014). The issue of the size of program populations is an important consideration in adaptation, with small populations and practices needing to collaborate to share expertise and realize the benefits of care management, while larger programs and populations should "embed" care managers in practices. The review also reported that team and change culture within individual practices were important factors in the acceptance and success of care management. In common with approaches suggested by Shadmi and Freund, Hong et al also recommended a combined approach to selecting and screening patients (Shadmi & Freund, 2013). This combined approach involves the combination of screening algorithms and clinician referral as complementary methods, but also applying algorithms and clinical screening criteria to multiple considerations. Screening algorithms have been used by a number of studies which specially target patients who are at risk of high future costs, but equally valid are algorithms that are targeted at the likelihood of hospitalizations and emergency department visits. The application of multiple screening applications helps to ensure the application of a more comprehensive definition of at risk patients. While referral is a useful process to allow physicians and clinicians to identify high risk patients, there may be bias in the referral process towards patients who are difficult to manage as opposed to being high risk.

Individuals who do not enroll or actively participate in care management may be labelled as "non amenable", and potentially excluded from consideration in the design of programs. As Wallace (Wallace, 2010) identified there are multiple types of engagement, and some highly engaged individuals may be highly selective in the interventions they see as suitable for themselves. This behavior may be seen as non-compliant by providers. It is therefore important to ensure that care management programs are not just designed for those who show favorable behaviors, and are targeted at those individuals. Such an approach risks excluding individuals with genuine health needs, who are highly engaged in their own health care and needs, who need direct support and outreach to encourage self-management and assist them in advocating for their health requirements. Patients such as those identified by Dettalo, who undertook self-management education but were dissatisfied with their health providers, could be excluded systematically from relevant programs if customizable programs are not provided, or where screening for patients is not comprehensive (Dattalo et al., 2012).

6.4 Study Strengths and Limitations

This study developed an approach to define engagement and to explore the factors influencing a patient's engagement in care management programs. As a research study it is seeking to build on the current knowledge and fulfill one of Gliner and Morgan's (Gliner & Morgan, 2000) characteristics of a good research problem, i.e. '*hold the promise of filling a gap in the literature'*. Quasi-experimental design such as employed here has certain limitations with respect to the validity of any findings, but these can be mitigated in part by the use of pre and post observations, multiple measures and time-periods, multiple populations and large sample base.

Two major advantages of the extensive use of secondary data are realized in this study, being low cost and unobtrusive (Weiner, Powe, Steinwachs, & Dent, 1990). Regarding external validity, the study draws from three distinct populations but all are from the State of Maryland. In addition, there are multiple effects from other programs and treatments. As the study proposes the development of a new measure, the CMPL score, steps were applied to begin to test the reliability and validity of the measure.

To mitigate against selection bias due to a non-randomized design the outcomes were tested using Propensity Score Matching (PSM), however the results may be subject to bias with respect to omitted variables. This relates to a key assumption in the PSM approach is conditional independence. This is that there are is a given set of covariates which are observable, not affected by the intervention, and the outcomes are independent of the assignment to 'treatment' or 'control' (Caliendo & Kopeinig, 2008). Specifically, any variables that affects an individual enrolling in care management and subsequent outcomes, are included in the model, and therefore, there are no unobserved variables affecting enrollment. The PSM caliper method censored patients who did not have a close match and therefore the choice of the parameters using this method will affect the level of censoring. The level of censoring was particularly pronounced for the Medicaid plan data in this study, but it was felt that the addition of the PSM nearest neighbor method which does not censor mitigated against this risk.

Patient engagement and participation is a current issue in managed care in the US. But it has not been well described or fully measured on a basis with available data such as routine claims or electronic medical records. This study sought to provide a stronger definition and practical measurement to aid the identification of influencing factors and thus provide for targeted

interventions in the future to improve the health status and treatment of patients with chronic conditions. The lack of any data regarding the care management interventions does however limit any direct conclusions with respect to specific interventions and programs being drawn.

The linkage of care management records to the claims data resulted in a number of duplicate records being deleted, which introduced potential bias, although this would be small as the affected members were less than 0.77% of the study population (141 of 18413). The missing care management records for moderate risk members may reflect a recording bias, however these omissions were due to patients who could not be followed up immediately following each screening period. The demographic data was compared for these members and discussed with the care management team, no systematic bias was found and therefore the censoring of data was assumed to be random.

Survey responses, such as those for the Personal Wellness Profile (PWP), are subject to response bias, non-response bias, and censoring. The survey was only available for the Employee health plan, and represented 30.9% of the screened population for that plan. The survey responses had a higher proportion of care management enrollees than for the whole screened population, a higher proportion of women, and the respondents were younger with a lower level of chronic conditions and multimorbidity. These findings are similar to those found by Merrill and Hull for the PWP and observed that participants in the survey may be more likely to submit health claims but less likely to participate in wellness programs (Merrill & Hull, 2013). The use of the responses to this survey should therefore be considered in the context of these biases. Temporal effects may be considered to provide additional confounding, with results taken at different intervals prior to the

screening for care management. The provision of a model using these data, and models excluding these data items should form the basis of a comparative evaluation to understand the potential for bias to or against respondents of such a survey.

More generally, temporal effects are difficult to assess with limited data. Further years of data would allow better assessment of the temporal effects, particularly the effect that previous decisions to enroll in care management have on future decisions. This study was not able, for example, to assess if individuals responded adversely to frequent requests to enroll in health programs.

External factors may have been confounders during the data collection period, including changes in the health care system (Andersen, 1995). The time period was chosen in consultation with colleagues from JHHC, to be relatively stable and therefore minimize the potential effects of information system redesign, as well as changes to care management program design and screening approaches. Such effects would need to be considered for longer term studies.

The Care Management data did not contain any data specific to the types of intervention undertaken, or specific responses from the member. Details of case management interventions are only available as written text within the case notes. This therefore means that this study did not make any attempt to categorize the types of interventions, only whether members had chosen to participate in a case management program.

The use of secondary data provides for potential limitations in the study, in particular the additional data provided by the Personal Wellness Profile represents a response bias to those members who completed the survey. The variables in these data were therefore only used to explore the relationship between factors and were not used in the exploratory analysis or the subsequent models.

The principal outcome measured was the second year healthcare costs following screening. There are potential concerns that healthcare costs may be incomplete, or include variance that is not directly attributable to the care or program, but to variance in prices and non-standardized fee-for-service schedules. Utilization measures (hospitalization, outpatient and emergency room visits) were added as it is argued they have a more direct measure of impact on programs (Serxner, Baker, & Gold, 2006) than costs for evaluation. The use of two years of data in this study could potentially increase the risk of regression to the mean and selection bias. The 12 months of data prior to screening (baseline), and 12-month post screening should be increased in a future study to establish an enhanced baseline and observation period. More detailed analysis could have been made using per member per month costs. The use of paired matching (PSM) methods was utilized to mitigate against selection bias, however the use of these retrospective techniques is still relatively recent and a more complete understanding of bias in these techniques may not be fully understood (Grossmeier et al., 2013).

6.5 Study Implications

This study proposed the creation of a measure for participation, and the incorporation of such a measure into predictive models for high risk case management identification and stratification. The study presents a use of existing data to enhance the current processes within JHHC for identifying high risk patients and the issues associated with their participation and enrolment in care management programs. This represents an advance in the use of claims and administrative data that could be applied to other populations and for care management in other organizations. The identification of key patient factors and changes in the predictive models also provides an opportunity to advance the risk prediction in the healthcare environment through the use of models more applicable to the general population.

The literature regarding care management has found in some studies that quality of care and patient satisfaction is higher amongst those who enroll and participate. But the mixed results with regard to cost savings presents a challenge to perpetuating care management in its current form. The recent report from the Commonwealth Fund, highlights the challenges facing care management programs, and the need for ongoing evaluation and refinement (Blumenthal et al., 2016). The methods and results of this study reflect the need to utilize multiple tools to screen and identify patients in need of care management, and likewise evaluation of the programs requires consideration using multiple metrics. The patient factors found to be associated with participation, such as the reduction in enrollment in care management as multimorbidity increases, illustrates the need to ensure that programs are appropriately designed for, and advocated to, these high need populations.

6.6 Areas for Future Research

This chapter has raised a number of potential questions to be investigated in further research. These include investigations involving potential new data, further examination of effects found in the study, and a better understanding of potential alternative care management approaches for high multimorbidity patients.

The increased recording and availability of electronic health record (EHR) and personal health record (PHR) data provides a potential to investigate additional variables that describe other elements of engagement and participation. The study identified specific items provided by the personal wellness profile that could add explanatory power to a risk model, if they were collected from a higher proportion of patients. The claims data did not allow for the specific nature of the care management intervention to be identified, therefore the collection and identification of data that delineates normal process of care and that attributed to the care management programs, such that the direct and indirect effects of the care management process could be studied. It would also be advantageous to record the type of care management intervention, whether the patient or the plan had dis-enrolled, and the extent to which the intervention had been completed.

The use of the SAS statistical software limited the creation of sub-population groupings to Principal Component Cluster Analysis. Alternative classification approaches to creating sub-population groups such as Classification and Regression Trees (Brieman, Friedman, Olshen, & Stone, 1993) would provide options for comparison.

The race and referral effects could be investigated further to understand if these are observable in other care management populations, particularly Medicaid, and if these are related to race and gender concordance between patients, family, providers, and social support. The referral effect could be investigated to examine if it is specific to providers, care managers or result of a multi-disciplinary care team approach. This study was not able to examine whether or how participation was linked to social factors, and whether patients in poverty or with scarce resources are more likely to enroll.

In considering patient cognitive ability, does the concept of 'Bandwidth' explain why patients with high multimorbidity are less likely to enroll more generally that just those in poverty? Do patients with high multimorbidity, and interacting with multiple care professionals, lead them to be more likely to decline additional services such as care management?

Further understanding needs to be gained to understand why patients do not enroll in care management, and particularly those with high multimorbidity for who the case management programs have been targeted. Such a study would also need to examine whether existing care management approaches are appropriate for the very highest multimorbid patients, given the findings of this study, that higher multimorbid patients are less likely to enroll in care management and have higher costs if they do. This study was not able to examine the effect of alternative interventions for high multimorbid patients such as Case Management, Telephonic Case Management, watchful waiting, Medical Care homes and Primary Care Medical Care homes (Wise, Bahl, Mitchell, West, & Carli, 2006). Finally, this study was only able to observe 12 months' post screening in the outcomes analysis, but such a time period may not be sufficient

to realize the benefits of care management sufficiently. It is therefore important to gain an understanding of over what time periods (continuous and discontinuous) should benefits of different care management programs be expected to be delivered.

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8 APPENDICES

8.1 Variable list

Variable	Type	Description	Source
Member demographic data			
Age	Continuous	Patient age in years	JHM Population Health Data
Gender	Dichotomous	Patient gender, Male/Female	*ditto*
Zip Code	Categorical	5-digit Patient's residential Zip code.	*ditto*
Region	Categorical	Patient's residential County: Baltimore City Region = Baltimore City Central Region = Carroll, Harford, Baltimore, Howard, Anne Arundel Southern Region = Calvert, Charles, St Mary's Western Region = Garrett, Allegany, Washington, Frederick Upper Shore Region = Caroline, Cecil, Kent,Queen Anne's, Talbot Lower Shore Region = Dorchester, Somerset, Wicomico, Worcester Other Region = Any Other	*ditto*
JHHC Line of Business	Categorical	The JHHC Health Plan of the patient. Plans include EHP or Priority Partners	*ditto*
Duration of plan eligibility	Categorical/ Continuous	Length of time the patient has been eligible for the health plan.	*ditto*

Variable	Type	Description	Source
Ethnicity/Race	Categorical	Patient's ethnicity/race: non-Hispanic White, non-Hispanic Black, Hispanic, Asian/Pacific Islander, American Indian/Alaska Native, and Unknown/Other	*ditto*
Social/economic status	Categorical		JHM Population Health Data
Total Cost of Care	Continuous	Annualized total cost of care	*ditto*
Phamacy Cost	Continuous	Annualized total cost of pharmacy	*ditto*
Utilization data			
Primary care type	Categorical		JHM Population Health Data / JH Community Physicians EMR
Secondary care type	Categorical		*ditto*
Primary Care visits	Continuous	Annualized count of Primary Care visits	*ditto*
Specialist Care encounters	Continuous	Annualized count of Specialist Care encounters	*ditto*
ER Visits	Continuous	Annualized count of Emergency Room Visits	*ditto*
Hospital admissions	Continuous	Annualized count of Hospital admissions	*ditto*
Care Management			
Care Management Enrollment status	Dicotomous	Enrolled, Not Enrolled	JHM Population Health Data
Duration of Enrollment	Continuous	Count during year of days in enrollment	*ditto*

Variable	Type	Description	Source
Gaps in Enrollment	Continuous	Count during year of breaks in enrollment	*ditto*
Screening Stratification	Categorical	The risk stratification assigned to the patient by the JHHC algorithm. Values include High, Moderate, Low	JHM Population Health Data
Examinations/Tests			
HbA1C test marker	Dicotomous	Hemoglobin A1c (HbA1C) test undertaken: Yes, No	JHM Population Health Data / JH Community Physicians EMR
HbA1C value	Continuous	Hemoglobin A1c (HbA1C) test value	*ditto*
Blood pressure	Categorical		*ditto*
BMI	Continuous	Body Mass Index	*ditto*
Eye examination	Dicotomous	Annual ophthalmic eye examination: Yes, No	*ditto*
Foot examination	Dicotomous	Annual foot examination: Yes, No	*ditto*
Primary Care Provider	Categorical	Profile of Primary Care Provider, Ethnicity/Race and age group.	*ditto*
ACG Input/Output			
Diagnoses Codes	Categorical	ICD9CM diagnoses codes attributed to an individual	JHM Population Health Data
Pharmacy Codes	Categorical	NDC pharmacy codes attributed to an individual	*ditto*

Variable	Type	Description	Source
adg_codes	Categorical	Aggregated Diagnosis Groups (ADG) attributed to patient: 01-34	*ditto*
adg_vector	Categorical	Aggregated Diagnosis Groups represented as a binary vector.	JHM Population Health Data
edc_codes	Categorical	Expanded Diagnosis Clusters (EDC) attributed to patient	*ditto*
rxmg_codes	Categorical	Rx-Defined Morbidity Groups (Rx-MGs) attributed to patient	*ditto*
major_rxmg_codes	Categorical	Major Rx-Defined Morbidity Groups (Rx-MGs) attributed to patient	*ditto*
major_adg_count	Continuous	Count of Major Aggregated Diagnosis Groups	*ditto*
frailty_flag	Dicotomous	Marker indicating if the patient has a diagnosis falling within any 1 of 11 clusters that represent medical problems associated with frailty	*ditto*
hospital_dominant_count	Continuous	A count of Hospital dominant conditions, diagnoses that are associated with a greater than 50 percent probability among affected patients of hospitalization in the next year	*ditto*
chronic_condition_count	Continuous	A count of EDCs containing trigger diagnoses indicating a chronic condition with significant expected duration and resource requirements.	*ditto*
asthma_condition	Dicotomous	Asthma diagnosis marker, A flag indicating if this patient has this medical condition and how it was indicated (NP=Not Present, ICD=ICD Indication, Rx=Rx Indication, BTH=ICD and Rx Indication, TRT=Meets Dx/Rx treatment criteria).	*ditto*
arthritis_condition	Dicotomous	Arthritis diagnosis marker	*ditto*
CHF_condition	Dicotomous	Congestive Heart Failure diagnosis marker	*ditto*

Variable	Type	Description	Source
COPD_condition	Dicotomous	Chronic Obstructive Pulmonary Disease diagnosis marker	*ditto*
CRF_condition	Dicotomous	Chronic Renal Failure diagnosis marker	JHM Population Health Data
depression_condition	Dicotomous	Depression diagnosis marker	*ditto*
diabetes_condition	Dicotomous	Diabetes diagnosis marker	*ditto*
hyperlipidemia_condition	Dicotomous	Hyperlipidemia diagnosis marker	*ditto*
hypertension_condition	Dicotomous	Hypertension diagnosis marker	*ditto*
IHD_condition	Dicotomous	Ischemic Heart Disease diagnosis marker	*ditto*
low_back_pain_condition	Dicotomous	Low Back Pain diagnosis marker	*ditto*
unscaled_total_cost_resource_index	Continuous	Unscaled Total Cost Resource Index. ACG Predictive Model (ACG-PM) Predicted Resource Index (PRI) for Total Cost -- the estimated total costs (including pharmacy costs) for this patient for the year following the observation period. Based upon a reference database (with a mean of 1.0), the predicted value is expressed as a relative weight.	*ditto*
rescaled_total_cost_resource_index	Continuous	Rescaled Total Cost Resource Index. The Total Cost Resource Index rescaled so that the local population mean is 1.0. Subgroup analyses provide comparisons to local norms.	*ditto*
probability_high_total_cost	Continuous	ACG Predictive model Probability High Total Cost. ACG-PM Probability Score for total cost, the probability that the patient will have high total costs (including pharmacy costs) in the year following the observation period.	*ditto*

Variable	Type	Description	Source
unscaled_pharmacy_cost_resource_index	Continuous	ACG Predictive model Unscaled Pharmacy Cost Resource Index. ACG-PM PRI Score for Pharmacy Costs -- the estimated pharmacy costs for this patient for the year following the observation period. Based upon a reference database (with a mean of 1.0), the predicted value is expressed as a relative weight.	JHM Population Health Data
rescaled_pharmacy_cost_resource_index	Continuous	ACG Predictive model Rescaled Pharmacy Cost Resource Index. Indicates that this patient has high risk of an unexpectedly high pharmacy cost in the year following the observation period.	*ditto*
probability_high_pharmacy_cost	Continuous	ACG Predictive model Probability High Pharmacy Cost. Probability that the patient will have unexpectedly high pharmacy costs in the year following the observation period.	*ditto*
JHHC Care Management Program Patient Survey data			
Activation Score	Continuous	Score from Patient Activation Measure (PAM), with a theoretical range from 0 to 100 (increasing activation)	JHHC PAM
Physical Health Composite Score (PCS)	Continuous	Composite score with range from 0 to 100, zero score indicates lowest level of health, 100 indicates the highest level of health.	JHHC SF-12
Mental Health Composite Scores (MCS)	Continuous	Composite score with range from 0 to 100, zero score indicates lowest level of health, 100 indicates the highest level of health.	*ditto*

8.2 Personal Wellness Profile

Variable	Type	Description	Source
General Health Perception (PWP #2)	Ordinal	Personal Wellness Profile Concise Assessment questionnaire. #2 General Health: excellent; very good; good; fair; poor.	JHHC PWP
Social support (PWP #29)	Dicotomous	Personal Wellness Profile Concise Assessment questionnaire. #29 Social support: yes, no	
Last physical exam (PWP #34)	Ordinal	Personal Wellness Profile Concise Assessment questionnaire. #34 Last physical exam, within the last: year, two years, three years, four years, five or more.	
Preventive exams (PWP #37)	Dicotomous (3 variables)	Personal Wellness Profile Concise Assessment questionnaire. #37 Preventive exams: bowel exam, dental exam, flu shot.	
Readiness to change (PWP #38)	Ordinal (5 point scale, 7 variables)	Personal Wellness Profile Concise Assessment questionnaire. #38 Readiness to change: 1.be physically active; 2.practice good eating habits; 3.avoid smoking or using tobacco; 4.lose weight, or maintain healthy weight; 5.handle stress well; 6.avoid alcohol or drink in moderation; 7.live an overall healthy lifestyle.	

8.3 Additional Results

This section contains additional results to those in Chapter 5. These represent supplemental analysis, or detailed results where summaries were provide in the results chapter.

8.3.1 Missing Data

Case management enrollment outcomes were present for all high risk ("Level 1") screened patients, but missing for some moderate risk ("Level 2") patients. For members screened from the Priority Partners plan there were 5451 records without a recorded outcome, and 2871 records with an outcome. It was assumed the members without an outcome were not followed up during the screening period, but were subsequently reentered into the screening algorithm the succeeding month. This assumption was confirmed by the case management team. Key characteristics of the records were examined to indicate any bias in the underlying populations. Table 8-1 shows the mean (and standard deviation) of the variables. These results were examined to determine any systematic bias in the collection of Case management enrollment outcomes.

Table 8-1: Demographic Characteristics: Medicaid plan, CM Moderate Risk 'Level 2' Screened, Mean (sd)

Characteristic	*CM Records with missing CM Outcome*		*CM Records with CM Outcome*	
N	5451		2871	
Female	0.7265	(0.4458)	0.7548	(0.4303)
Region				
Baltimore City	0.3654	(0.4816)	0.5556	(0.4970)
Baltimore County	0.1257	(0.3315)	0.0878	(0.2830)
Eastern Shore	0.2620	(0.4397)	0.1877	(0.3906)
Southern	0.1624	(0.3688)	0.1069	(0.3091)
Age at Screening	45.9518	(11.064)	43.3696	(12.494)
Race				
Black	0.4861	(0.4999)	0.6047	(0.4890)
White	0.4364	(0.4960)	0.3197	(0.4665)
Other	0.0360	(0.1862)	0.0300	(0.1705)
Chronic Conditions	4.2434	(2.4212)	4.1365	(3.0081)
Major ADGs	1.9176	(1.3224)	2.0596	(1.5853)
Frailty	0.2491	(0.4325)	0.2720	(0.4451)
Probability IP Hospitalization	0.2008	(0.1415)	0.2261	(0.1859)
Rescaled Total cost index	5.5923	(3.0042)	6.1651	(4.5205)
Generic Drug count	15.6894	(7.6085)	14.4657	(8.7739)
Unique Provider count	4.3244	(2.7731)	4.3265	(2.8998)
Specialty count	3.5654	(2.0473)	3.4404	(2.0900)
Plan Enrollment				
Enrolled > 6mth	0.8586	(0.3485)	0.8513	(0.3559)
Enrolled > 12mth	0.8011	(0.3992)	0.7388	(0.4394)
Condition Prevalence				
Asthma	0.5584	(0.4966)	0.5340	(0.4989)
Rheumatoid Arthritis	0.0330	(0.1787)	0.0313	(0.1743)
Congestive Heart Failure	0.0915	(0.2884)	0.1153	(0.3194)
Depression	0.5252	(0.4994)	0.4483	(0.4974)
Diabetes	0.5505	(0.4975)	0.4044	(0.4909)
Lipidemia	0.5241	(0.4995)	0.4131	(0.4925)
Hypertension	0.7489	(0.4337)	0.6621	(0.4731)
Ischemic Heart Disease	0.1048	(0.3063)	0.1069	(0.3091)

Mean (standard deviation)

8.3.2 Logistic Regression – Medicaid plan, Second outcomes

The following tables Table 8-2 and Table 8-3 are the outputs of logistic regression models from the Medicaid data. The dependent variable is the second outcome (enrollment in care management program, or non-enrollment) for a patient, given an initial outcome. Table 8-2 shows the odd ratios for the second outcome for all patients who had enrolled in care management following the first screening.

Table 8-2 Impact of factors on predicting member's acceptance to join CM program: Medicaid population, Second Outcome where First accepted CM

Effect	Odds Ratio Estimate	95% CL	
Gender Male vs Female	1.095	0.825	1.454
Region			
Central vs Baltimore City	3.196	0.950	10.759
County vs Baltimore City	1.551	1.001	2.405
Eastern Shore vs Baltimore City	1.531	1.089	2.151
Other vs Baltimore City	1.486	0.187	11.806
Southern vs Baltimore City	1.82	1.260	2.629
Western vs Baltimore City	1.668	0.829	3.354
Age 35-64 (base 18-34)	1.233	0.904	1.682
Race			
Black vs White	0.953	0.712	1.274
Other vs White	1.645	0.495	5.472
Unspecified vs White	0.846	0.5	1.433
Primary Care Provider Multiple vs 1	0.465	0.357	0.606
Chronic Conditions (vs none)			
1	2.056	0.940	4.498
2	1.998	0.954	4.183
3	1.803	0.843	3.857
4	2.046	0.919	4.555
5	1.161	0.533	2.529
6+	0.885	0.407	1.923
Major ADG (vs none)			
1	1.242	0.628	2.457

Effect	Odds Ratio Estimate	95% CL	
2	0.938	0.482	1.826
3	0.822	0.416	1.623
4	0.55	0.278	1.087
Frailty	1.335	1.019	1.748
Referral	0.599	0.312	1.149
Generic drug count	0.993	0.975	1.011
Unique Provider Count	0.936	0.862	1.016
Number of Specialties	1.103	0.975	1.248
No Generalist	1.002	0.540	1.860
Condition			
Asthma	1.046	0.803	1.363
Rheumatoid Arthritis	0.602	0.343	1.058
Congestive Heart Failure	0.788	0.567	1.094
Depression	1.096	0.831	1.447
Diabetes	0.818	0.623	1.075
Disorders of Lipid Metabolism	1.574	1.154	2.147
Hypertension	1.283	0.938	1.757
Ischemic Heart Disease	1.044	0.692	1.575
Enrollment in Health Plan			
6 months	1.011	0.601	1.700
12 months	0.463	0.319	0.671

Medicaid plan, Screened for Care Management High and Moderate Risk
Second Outcome where First accepted CM, n = 2814, probability = 0.8813
Baseline odds for a Female aged 18-34, White, Baltimore City = 13.7701
Abbreviations: CL, confidence limit

Table 8-3 shows the odd ratios for the second outcome for all patients who had not enrolled in care management following the first screening. The dependent variable is the second outcome (enrollment in care management program, or non-enrollment) for a patient, given an initial outcome.

Table 8-3 Impact of factors on predicting member's acceptance to join CM program: Medicaid population, Second Outcome where First declined CM

Effect	Odds Ratio Estimate	95% CL	
Gender Male vs Female	1.092	0.942	1.266
Region			
Central vs Baltimore City	0.656	0.366	1.177
County vs Baltimore City	0.818	0.651	1.027
Eastern Shore vs Baltimore City	0.77	0.645	0.92
Other vs Baltimore City	1.011	0.485	2.108
Southern vs Baltimore City	0.916	0.748	1.122
Western vs Baltimore City	0.718	0.516	0.997
Age 35-64 (base 18-34)	0.889	0.737	1.073
Race			
Black vs White	1.072	0.927	1.24
Other vs White	1.187	0.757	1.86
Unspecified vs White	1.05	0.784	1.406
Primary Care Provider Multiple vs 1	1.536	1.34	1.761
Chronic Conditions (vs none)			
1	1.441	0.66	3.148
2	1.25	0.578	2.703
3	1.773	0.826	3.805
4	1.654	0.769	3.558
5	1.878	0.869	4.061
6+	1.785	0.827	3.853
Major ADG (vs none)			
1	0.749	0.456	1.231
2	0.780	0.479	1.272
3	0.887	0.544	1.447
4	0.805	0.495	1.31
Frailty	1.190	1.039	1.363

Effect	Odds Ratio Estimate	95% CL	
Referral	2.697	1.881	3.866
Generic drug count	0.997	0.988	1.007
Unique Provider Count	1.026	0.984	1.07
Number of Specialties	0.997	0.936	1.062
No Generalist	0.874	0.608	1.258
Condition			
Asthma	1.122	0.974	1.292
Rheumatoid Arthritis	1.012	0.738	1.388
Congestive Heart Failure	1.237	1.056	1.449
Depression	1.146	0.991	1.326
Diabetes	1.093	0.942	1.268
Disorders of Lipid Metabolism	0.960	0.821	1.123
Hypertension	1.022	0.85	1.228
Ischemic Heart Disease	1.035	0.864	1.24
Enrollment in Health Plan			
6 months	0.842	0.637	1.115
12 months	1.760	1.462	2.119

Medicaid plan, Screened for Care Management High and Moderate Risk
Second Outcome where First declined CM, n = 5009, probability = 0.2715
Baseline odds for a Female aged 18-34, White, Baltimore City = 0.0537
Abbreviations: CL, confidence limit

8.3.3 Logistic Regressions – Random Effects Models

The following tables, Table 8-4, Table 8-5, and Table 8-6 show the odds ratios produced by the three random effects models: ‘region’; ‘care manager’; and ‘region’ with ‘care manager’ level. The three models were derived to test for global effects that were independent of patient level effects. Selective results are shown in section 5.1.3 Effects of Region and Care Manager.

Table 8-4 Impact of factors on predicting members' acceptance to join CM program: Care Manager Nested Model, Medicaid Plan

Effect	Odds Ratio Estimate	95% CL	
Gender Female vs Male	1.068	0.934	1.222
AgeBand3 18-34 v 35-64	1.401	1.21	1.622
Race			
Black vs White	1.347	1.186	1.530
Other vs White	0.783	0.547	1.122
Unspecified vs White	1.194	0.915	1.558
Primary Care Provider 1 v Multiple	1.659	1.427	1.929
Chronic Condition			
1 vs 0	1.917	1.365	2.691
2 vs 0	1.487	1.144	1.933
3 vs 0	1.416	1.135	1.766
4 vs 0	1.234	1.008	1.510
5 vs 0	1.314	1.080	1.599
6+ vs 0	1.142	0.939	1.389
Major ADG			
1 vs 0	1.926	1.478	2.509
2 vs 0	1.418	1.167	1.724
3 vs 0	1.511	1.269	1.800
4 vs 0	1.223	1.033	1.448
Frailty N vs Y	0.982	0.861	1.120
Referral	0.721	0.562	0.926
Generic drug count	0.984	0.975	0.992
Unique Provider Count	0.973	0.929	1.020
Number of Specialties	1.115	1.043	1.192
No Generalist N vs Y	0.878	0.72	1.069
Enrollment in Health Plan			
6 months	1.236	1.070	1.428
12 months	1.317	1.003	1.730

Medicaid plan, Screened for Care Management High and Moderate Risk
Baseline odds for a Male aged 35-64, White = 0.3300
Abbreviations: CL, confidence limit

Table 8-5 Impact of factors on predicting members' acceptance to join CM program: Region Nested Model, Medicaid Plan

Effect	Odds Ratio Estimate	95% CL	
Gender Female vs Male	1.055	0.929	1.198
AgeBand3 18-34 v 35-64	1.296	1.126	1.492
Race			
Black vs White	1.419	1.253	1.607
Other vs White	0.860	0.610	1.211
Unspecified vs White	1.186	0.924	1.522
Primary Care Provider 1 v Multiple	1.589	1.377	1.833
Chronic Condition			
1 vs 0	1.801	1.279	2.535
2 vs 0	1.400	1.071	1.829
3 vs 0	1.371	1.097	1.714
4 vs 0	1.297	1.059	1.589
5 vs 0	1.304	1.077	1.578
6+ vs 0	1.234	1.023	1.487
Major ADG			
1 vs 0	1.759	1.371	2.256
2 vs 0	1.305	1.083	1.572
3 vs 0	1.321	1.120	1.558
4 vs 0	1.161	0.990	1.362
Frailty N vs Y	0.958	0.847	1.083
Referral	2.807	2.323	3.391
Generic drug count	0.988	0.979	0.997
Unique Provider Count	0.983	0.941	1.027
Number of Specialties	1.085	1.019	1.156
No Generalist N vs Y	0.876	0.777	0.987
Condition			
Asthma	0.728	0.539	0.983
Rheumatoid Arthritis	1.043	0.882	1.234
Congestive Heart Failure	0.920	0.814	1.040
Depression	0.910	0.801	1.033
Diabetes	0.962	0.838	1.104
Disorders of Lipid Metabolism	0.800	0.697	0.917
Hypertension	0.919	0.756	1.116
Ischemic Heart Disease	0.953	0.791	1.148
Enrollment in Health Plan			
6 months	1.044	0.910	1.197
12 months	1.224	0.939	1.595

Medicaid plan, Screened for Care Management High and Moderate Risk
Baseline odds for a Male aged 35-64, White = 0.1137
Abbreviations: CL, confidence limit

Table 8-6 Impact of factors on predicting members' acceptance to join CM program: Region (Care Manager) Nested Model, Medicaid Plan

Effect	Odds Ratio Estimate	95% CL	
Gender Female vs Male	1.056	0.921	1.210
AgeBand3 18-34 v 35-64	1.325	1.137	1.544
Race			
Black vs White	1.370	1.202	1.561
Other vs White	0.796	0.555	1.143
Unspecified vs White	1.200	0.919	1.568
Primary Care Provider 1 v Multiple	1.678	1.442	1.952
Chronic Condition			
1 vs 0	1.670	1.158	2.409
2 vs 0	1.311	0.983	1.749
3 vs 0	1.294	1.017	1.647
4 vs 0	1.152	0.927	1.431
5 vs 0	1.245	1.012	1.531
6+ vs 0	1.102	0.901	1.347
Major ADG			
1 vs 0	1.939	1.477	2.545
2 vs 0	1.438	1.174	1.761
3 vs 0	1.528	1.278	1.827
4 vs 0	1.224	1.032	1.451
Frailty N vs Y	0.997	0.873	1.137
Referral	0.739	0.575	0.948
Generic drug count	0.986	0.976	0.996
Unique Provider Count	0.974	0.929	1.021
Number of Specialties	1.113	1.040	1.190
No Generalist N vs Y	1.029	0.904	1.172
Condition			
Asthma	0.720	0.523	0.992
Rheumatoid Arthritis	0.992	0.831	1.186
Congestive Heart Failure	0.952	0.834	1.087
Depression	1.064	0.927	1.221
Diabetes	1.050	0.904	1.219
Disorders of Lipid Metabolism	0.761	0.657	0.883
Hypertension	0.884	0.718	1.089
Ischemic Heart Disease	0.866	0.711	1.056
Enrollment in Health Plan			
6 months	1.234	1.068	1.426
12 months	1.340	1.018	1.762

Medicaid plan, Screened for Care Management High and Moderate Risk
Baseline odds for a Male aged 35-64, White = 0.3893
Abbreviations: CL, confidence limit

8.3.4 Year 2 Outcomes

The following tables show alternative analyses for second year (following initial screening) from section 5.4. These were provided to colleagues in JHHC earlier in the study to provide feedback and suggestions for improvement or issues to investigate.

Table 8-7 shows the overall mean costs (crude and modelled/expected) in the year after initial care management screening, for the 3 health plans, divided between patients who enrolled and those who did not enroll in care management. The Employee and Medicaid health plans show a lower mean cost in year 2 for those who enrolled in a Care Management program compared to those who did not enroll. The Family Health plan had a higher cost for Care Management enrollees compared to non-enrollees. The adjusted mean costs are shown in the table below, together with the adjusted Inpatient Rate and Emergency Rate in year 2.

Table 8-7 Year 2 Total Cost by Health Plan, Care Management Enrolled v Not Enrolled

Plan/Participation	N	Year 2 Mean Cost $	(95% CI)	Year 2 Adjusted Cost $	(95% CI)
Employee Health Plan					
CM Enrolled	923	20002.97	(17058-22948)	21095.32	(20014-22177)
Not Enrolled	1442	23315.31	(20966-25664)	25328.72	(24406-26252)
Medicaid Health Plan					
CM Enrolled	2331	26644.27	(24809-28479)	24730.17	(24097-25364)
Not Enrolled	2935	29372.54	(27819-30926)	28797.62	(28241-29354)
Family Health Plan					
CM Enrolled	581	31155.94	(27265-35047)	31413.93	(29968-32860)
Not Enrolled	1122	29431.62	(26900-31964)	31292.32	(30236-32349)

CI, Confidence Interval, CM, Care Management
Adjusted: Sex, Age, Major ADG count, Year1 Cost
Excludes patients with zero year 2 costs

Table 8-8 Mean Cost by Health Plan, Care Management Enrolled v Not Enrolled

Plan/Participation	N	Year 2 Mean Cost $	(95% CI)	Pr>|t|	Year 2 Expected Cost $	(95% CI)	Pr>|t|
Employee Health							
CM Enrolled	923	20002.97	(17057-22948)	<.0001	20623.10	(19480-21765)	<.0001
Not Enrolled	1442	23315.31	(20966-25664)	<.0001	23742.92	(22769-24715)	<.0001
Medicaid Health							
CM Enrolled	2331	26644.27	(24809-28479)	<.0001	25814.00	(25133-26494)	<.0001
Not Enrolled	2935	29372.54	(27818-30926)	<.0001	28475.83	(27873-29078)	<.0001
Family Health Plan							
CM Enrolled	581	31155.94	(27264-35047)	<.0001	33904.45	(32476-35332)	<.0001
Not Enrolled	1122	29431.62	(26899-31963)	<.0001	31019.27	(29937-32100)	<.0001

CI, Confidence Interval, CM, Care Management
Expected: Sex, Age, Major ADG count, Care Management Level, Year1 Cost
Excludes patients with zero year 2 costs

The adjusted mean costs are shown again in the table below, together with the adjusted Inpatient Rate and Emergency Rate in year 2.

Table 8-9 Table Year 2 Mean Cost, Inpatient Rate, ER Rate by Health Plan, Care Management Enrolled v Not Enrolled

Plan/Participation	N	Year 1 Mean Cost $	Year 2 Mean Cost $*	Inpatient Rate*	Emergency Room rate*
Employee Health Plan					
CM Enrolled	923	21320.77	20002.97	0.481	1.461
Not Enrolled	1442	29970.53	23315.31	0.590	1.536
Medicaid Health Plan					
CM Enrolled	2331	27168.33	26644.27	0.756	2.411
Not Enrolled	2935	34789.56	29372.54	0.919	2.611
Family Health Plan					
CM Enrolled	581	39949.7	31155.94	0.734	1.232
Not Enrolled	1122	39536.76	29431.62	0.705	1.123

*Adjusted: Sex, Age, Major ADG count, Year1 Cost
Excludes patients with zero year 2 costs

Table 8-10 and Table 8-11 show two options of sub-group analysis for the three plan populations, which were produced for JHHC colleagues to review, prior to the PSM analysis being produced. The first shows grouping that reflect the structures of the existing analytical reports, i.e. whether patients were identified for screening by the algorithm, or if they had been referred, and if they were screened for high risk 'level 1' or moderate risk 'level 2'. The second table shows the sub-groups derived from the factor and cluster analyses, based on the number of chronic conditions and major ADGS a patient had.

Table 8-10: Mean Cost by Health Plan, Care Management Enrolled v Not Enrolled, by Care Management Level and Screened by Algorithm (or Referral)

Plan/Participation	N	Year 2 Mean Cost $	(95% CI)	Year 2 Expected Cost $	(95% CI)
Employee Health Plan					
CM Enrolled					
Level 1 Algorithm	264	31920.05	(23013-40826)	31104.34	(29002-33206)
Level 1 Referral	225	19730.79	(15618-23843)	24576.58	(22939-26214)
Level 2 Algorithm	208	11114.96	(9452-12777)	11357.39	(10640-12074)
Level 2 Referral	190	7407.03	(6008-8805)	6700.68	(6312-7088)
Not Population Db	36	52143.64	(33475-70812)	46066.07	(32434-59697)
Not Enrolled					
Level 1 Algorithm	603	32844.19	(28192-37496)	31596.95	(30094-33099)
Level 1 Referral	75	27099.19	(13901-40296)	28143.02	(25248-31037)
Level 2 Algorithm	602	12124.49	(10881-13367)	14023.24	(13169-14877)
Level 2 Referral	86	7048.33	(3762-10334)	7529.56	(6420-8638)
Not Population Db	73	52144.24	(36615-67672)	52789.10	(47666-57911)
Medicaid Health Plan					
CM Enrolled					
Level 1 Algorithm	756	30838.58	(28049-33628)	31912.26	(30832-32991)
Level 1 Referral	713	24311.43	(20818-27803)	26335.73	(25505-27166)
Level 2 Algorithm	203	18618.32	(14340-22895)	13308.04	(12363-14253)
Level 2 Referral	409	8471.43	(7165-9777)	8374.90	(7781-8967)
Not Population Db	250	56861.76	(47736-65987)	44570.09	(42143-46996)
Not Enrolled					
Level 1 Algorithm	1279	38099.42	(35429-40769)	34117.56	(33386-34848)
Level 1 Referral	348	24242.34	(19823-28661)	29152.94	(27443-30862)

Plan/Participation	N	Year 2 Mean Cost $	(95% CI)	Year 2 Expected Cost $	(95% CI)
Level 2 Algorithm	842	17833.41	(16220-19446)	16251.26	(15635-16867)
Level 2 Referral	140	8186.28	(5715-10657)	9526.04	(8294-10757)
Not Population Db	326	39512.63	(33638-45387)	45330.59	(43341-47319)
Family Health Plan					
CM Enrolled					
Level 1 Algorithm	264	33834.52	(27900-39768)	35559.14	(33373-37744)
Level 1 Referral	203	24133.52	(18510-29756)	31245.91	(29517-32974)
Level 2 Algorithm	34	21940.37	(13752-30128)	14420.92	(12588-16253)
Level 2 Referral	12	5779.41	(3446-8112)	10133.88	(8377-11890)
Not Population Db	68	50806.78	(34835-66778)	49353.47	(44967-53739)
Not Enrolled					
Level 1 Algorithm	651	37397.07	(33655-41138)	34682.09	(33374-35989)
Level 1 Referral	102	27765.99	(17374-38157)	35570.51	(32718-38422)
Level 2 Algorithm	303	13470.74	(11989-14951)	17694.89	(16657-18732)
Level 2 Referral	9	8492.53	(3882-13102)	11381.69	(6612-16151)
Not Population Db	57	29589.31	(18330-40847)	54971.88	(47313-62630)

CI, Confidence Interval, CM, Care Management

Adjusted: Sex, Age, Major ADG count, Care Management Level, Year1 Cost

Excludes patients with zero year 2 costs

Table 8-11 shows the outcome analysis for the 4 groups suggested by exploratory factor and cluster analysis. The first group includes all members with less than 2 chronic conditions. The other three groups include all members with 2 or more chronic conditions, and increasing numbers of Aggregated Diagnoses Groups (ADGs), such that the most complex group consists of members with 5 or more ADGs combinations. A comparison of claims costs in the second year within each of these complexity groups was made to examine whether the cost differences between those who enrolled in care management; and those who did not enroll changes as complexity changes. The cost ratio is the Year 2 mean cost for those enrolled in a care management program divided by the mean cost of those who did not enroll.

The Medicaid plan had lower year 2 costs for those who enrolled for the two least complex groups of member, but the costs were higher amongst enrolled for the two complex groups. For the employee plan those who enrolled had lower costs for all but the most complex group. The Family health plan general produced higher costs in those who enrolled, except for the least complex group. While Table 8-11 showed that the overall costs for those who enroll are generally lower in year 2 that those who do not enroll, creating a breakdown by complexity suggests that as the complexity increases, care management enrolment increases claims costs over those who are not enrolled. The reduced costs are for those who are less multi-morbid within the population screened for care management.

Table 8-11 Mean Cost by Health Plan, Care Management Enrolled v Not Enrolled, by Count of Chronic Conditions and Major ADGs

Plan/Participation	N	Year 2 Mean Cost $	(95% CI)	Year 2 Adjusted Cost $	(95% CI)
Employee Health Plan					
CM Enrolled					
<2 Chronic Conditions	268	10579.13	(8508-12649)	12555.23	(11571-13539)
0-2 Major ADGs	489	18432.82	(15807-21058)	18568.24	(17624-19512)
3-4 Major ADGs	129	31008.39	(20625-41390)	34389.78	(30198-38581)
5+ Major ADGs	37	70643.21	(20288-120998)	58220.83	(46426-70015)
Not Enrolled					
<2 Chronic Conditions	267	12462.93	(9538-15387)	13854.77	(12643-15066)
0-2 Major ADGs	801	20584.87	(17509-23660)	20115.25	(19280-20950)
3-4 Major ADGs	306	35012.37	(28735-41289)	35899.65	(33142-38656)
5+ Major ADGs	68	45453.04	(32664-58241)	50595.07	(43701-57489)
Medicaid Health Plan					
CM Enrolled					
<2 Chronic Conditions	559	13304.71	(11352-15256)	14452.13	(13639-15264)
0-2 Major ADGs	828	20688.31	(18285-23090)	21111.68	(20413-21810)
3-4 Major ADGs	674	33614.48	(29927-37301)	31905.37	(30877-32932)
5+ Major ADGs	270	55127.34	(46356-63898)	48551.84	(45861-51242)
Not Enrolled					
<2 Chronic Conditions	367	15104.30	(12193-18015)	16397.10	(15336-17457)
0-2 Major ADGs	921	22844.16	(20399-25288)	20606.16	(19936-21275)
3-4 Major ADGs	1108	32327.76	(29808-34846)	31361.41	(30505-32217)
5+ Major ADGs	539	44167.91	(39650-48684)	44215.41	(42628-45801)
Family Health Plan					
CM Enrolled					
<2 Chronic Conditions	32	16694.27	(11001-22386)	22131.95	(18764-25499)
0-2 Major ADGs	244	23911.19	(18964-28858)	26701.01	(25469-27932)
3-4 Major ADGs	218	36013.98	(28062-43965)	35071.13	(33355-36786)
5+ Major ADGs	87	44620.77	(36311-52930)	55513.92	(49961-61066)
Not Enrolled					
<2 Chronic Conditions	42	21591.89	(4786-38397)	19827.27	(16623-23031)
0-2 Major ADGs	499	23318.14	(20388-26247)	22917.58	(22041-23794)
3-4 Major ADGs	444	32978.52	(28747-37209)	34482.54	(32908-36056)
5+ Major ADGs	137	42607.39	(32774-52440)	52735.41	(48287-57183)

CI, Confidence Interval, CM, Care Management
Adjusted: Sex, Age, Major ADG count, Care Management Level, Year1 Cost
Excludes patients with zero year 2 costs

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EDUCATION AND TRAINING

Doctor of Public Health (DrPH) (2016) Johns Hopkins University Bloomberg School of Public Health, Health Policy and Management, Baltimore, USA

Thesis: *Patient Involvement in Care Management Programs for Chronic Conditions*

Master of Applied Science (MAppSc) Distinction (2006) Sydney University, Faculty of Health Sciences, Australia

Thesis: *Evaluating and Refining the UK Healthcare Resource Groups*

Certificate, Institute of Health Services Management (1990) Southbank Polytechnic, London, UK

Bachelor of Science with Honors (BSc Hons) Class 2.1 (1987) Mathematics, Operational Research and Economics, University of Essex, UK

PROFESSIONAL EXPERIENCE

Johns Hopkins ACG International, Baltimore MD, USA
Director of Product Development 2013-Present
Responsibilities:

- Technical support of projects to insure appropriate installation, implementation and interpretation of the software and its results.
- Development of groupers-including country specific adaptation and development of local relative weights.
- Promotional efforts including presenting at international conferences.

Sutch Consulting International, Independent Casemix Consultant, Visiting Informatics Lecturer 2003-Present

- Clients include: Ontario Department of Health (Canada), Canadian Institute for Health Information (Canada), LAETA Pty Ltd (Australia), Health Ministry of Japan, Johns Hopkins Healthcare LLC (USA), Johns Hopkins University (USA), Quality Reimbursement Services (USA), Q&S (Italy), DBC Onderhoud (NL), Health Service Executive (Ireland), Children's Hospitals

Australasia, Department of Health (England), Swansea University, Royal College of Ophthalmology, British Burns Association, NHS Information Centre, York University (UK).

Johns Hopkins ACG International, Baltimore MD, USA
Senior Consultant 2006-2013

- Technical support of projects to insure appropriate installation, implementation, and interpretation of the software and its results.
- Development of software groupers – including country specific adaptations and development of local relative weights.
- Raise awareness and understanding of the system
- Provision of feedback to the Institution in order to support the Institution's research and development of the system and its applications.

National Health Service Information Authority, UK
Principal Casemix Consultant (Design) – Aug 2004 to July 2006
Responsibilities:

- Provide the leading expert advice and support on the development and use of casemix tools to the Department of Health (DH), Payment by Results.
- Oversee the developing requirements for analysis and interpretation of results
- Provide a knowledge base of casemix tools and policy areas to DoH and NHSIA
- Ensure the documentation of business processes and practices to aid the understanding of product development and implementation
- Oversee the development of casemix methodologies
- Formulate strategies for incorporating international tools and experience into the UK setting

National Health Service Information Authority, UK
Senior Consultant
Analytical and Statistical Services Manager – Sept 2000 to Aug 2004

NHS Information Authority Casemix Programme, UK
Casemix Consultant – April 1999 to Sept 2000
Responsibilities:

- Manage the Analytical & Statistical Services Team (10 Staff)
- Manage the provision of support to the Casemix Development Programme (Healthcare Resource Groups)
- Provide ad hoc advice and consultancy to the UK NHS as required.
- Provide seminars to all levels of NHS staff as required.

National Casemix Office, UK
Casemix Consultant - August 1995 to April 1999
Responsibilities:

- Manage the Service Level Agreement with the National Assembly for Wales.
- Provide Casemix related Policy advice, Hospital based consultancy, National Analysis and Information to NHS Wales.

Welsh Health Common Services Authority, Health Management Info. Systems
Casemix Project Manager - October 1993 to August 1995
Responsibilities:

- Project Manager for the Casemix Contracting Initiative
- Review and Implement a national casemix system
- Support the implementation of ICD10 in Wales
- Project Team member on the Welsh and English ICD10 Implementation Projects
- Provide seminars to Health Managers and Health Staff as required

Welsh Health Common Service Authority, Health Intelligence Unit
Senior Information Analyst - April 1991
Responsibilities:

- Provide national casemix analysis
- Support the development of the Welsh DRG Project
- Establish a national programme for Data Standards and Quality
- Management of 6 staff

North East Thames Regional Health Authority, Operational Research Department
Operational Research Consultant - October 1987
Responsibilities:

- Provide analytical support to the Regional Strategic Plan
- Provide support to contracts undertaken by the department
- Provide ad hoc consultancy work for customers

PUBLICATIONS

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B. Reid , S. Sutch *Comparing diagnosis-related group systems to identify design improvements*, Health Policy , Volume 87 , Issue 1 , Pages 82 – 91.

S. Sutch, *Casemix in the United Kingdom: From development to plans*, in J.Kimberly, G. Pouvourville, T. d'Aunno (eds), The Globalization of Managerial Innovation in Health Care, New York 2009, Cambridge University Press, pp. 34-50.

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C.; York N.; Sutch S.; Shaw R. *Hospital bed utilisation in the NHS, Kaiser Permanente, and the US Medicare programme: analysis of routine data,* Volume 327, British Medical Journal 29 November 2003

PRESENTATIONS

Conference Meetings/Presentations

S. Sutch, K. Kinder, K. Lemke, C. Pollack, *Coordination – can it be measured?* 32nd PCSI International Conference, Dublin, Republic of Ireland Oct 2016.

S. Sutch, *Population Health Management*, 2016 Triple Aim Congress, Jan van Es Instituut, 21 June 2016, Almere, The Netherlands.

S. Sutch, *Patient Participation in Care Management programs*, 2016 ACG System International Conference, April 17-19, 2016, San Diego CA

S. Sutch, *The enhanced use of primary care, ambulatory hospital data to identify patients for case management programs in England*, Wonka Europe 22-25 October 2015 Istanbul, Turkey

S. Sutch, C. Abrams, K. Lemke, A. Thompson, *Measuring and understanding patient coordination across the healthcare continuum.* 31st PCSI International Conference, The Hague, Netherlands 14-17 Oct 2015.

S. Sutch, C. Abrams, K. Lemke, *Predictive Models of the Risk of Hospital Admission and Re-Admission: Current and Future development.* 30th PCSI International Conference, 19-22 October 2014, Doha, Qatar.

S. Sutch, *The Predicting future resource use & risk of hospitalization for a general population in NHS England: Adapting US models & potential lessons for the US*, National Predictive Modeling Summit Nov 13-14, 2014 Washington DC

S. Sutch, C. Morris, *The creation of new models to predict future resource use and future risk of hospital admission for a general population in NHS England*. Johns Hopkins International Conference, April 27-30, 2014, Seattle WA.

S. Sutch, C. Morris, A. Thompson, *The creation of new models to predict future resource use and future risk of hospital admission for a general population in NHS England*, 29th PCSI International Conference, 18-21 September 2013, Helsinki, Finland.

S. Sutch, C. Abrams, K. Kinder, *Advances in predictive modelling: Informing the decision making process*, WONCA 2013 48th World Conference, Prague.

S. Sutch, A. Thompson, *The enhanced use of primary care, ambulatory hospital data to identify patients for case management programs in England*, 28th PCSI International Conference, 17-19 October 2012, Avignon, France.

S. Sutch, *Utilizing an Individual's Demographics and Pattern of Morbidity to Describe Expected Healthcare Costs*, 27th PCSI International Conference, 19-22 October 2011, Montreal, Canada.

S. Sutch, K. Kinder, *Using Case-Mix to Improve Equity and the Delivery of Primary Care*, 11 September 2011, 17th WONCA Europe Conference, Warsaw, Poland.

S. Sutch, *Utilizing an Individual's Demographics and Pattern of Morbidity to Describe Expected Healthcare Costs*, 26th PCSI Annual Conference, 15-18 September 2010, Munich, Germany.

S. Sutch, Conference Keynote: *Patient Classification beyond the hospital,* Australia Casemix Conference 2008, 16-19 November, Adelaide, Australia

S. Sutch, K. Lemke, J. Weiner, K. Kinder *The application of ACG Predictive models to the English Population for the purposes of funding allocation*, 24th PCSI International Conference, 9th – 11th October 2008, Lisbon, Portugal

K. Kinder, S. Sutch *Evaluating case-mix and predictive modelling measures within the British primary care sector*, 23rd PCSI International Conference, 7th – 10th November 2007, Venice, Italy

S. Sutch, *Revision of UK Casemix groups (HRG) for Paediatrics,* PCSE 21st International Working Conference, Singapore 2006

Sutch S. *ICF illustration library* Volume 82, Number 7, Bulletin of the World Health Organization July 2004

Sutch S.; Rogers H. *Financial Reforms In The English NHS And The Revision Of Casemix Groups*, National Casemix Working Conference, Kilkenny, Ireland 2004

The Analysis of Routine Data to Compare the English NHS, Kaiser Permanente, and the US Medicare programme, PCSI 20th International Working Conference, Budapest 2004

Sutch S.; Dredge R. *Financial Reforms in the English NHS and the Revision of Casemix Groups,* PCSE 19th International Working Conference, Washington 2003.

Sutch S.; Reid B. *An Assessment of the performance of Healthcare Resource Groups,* PCSE 19th International Working Conference, Washington 2003.

Roger R.; Wynn B.; Sutch S. *An External Review of the Joint Policy and Planning Committee Funding Formulae,* Joint Policy and Planning Committee, Toronto, Ontario 2003.

S. Sutch, *HRG Revision in England and Redesign for Paediatrics*, Proceedings of the 2nd Irish Casemix Conference, Dundalk 2003

Sutch S Spark V Benton P Farrell G Light M *The NHS Performance Analysis Toolkit,* 17th PCS/E conference and EFMI-WG1 Special Topic Conference, Brugge 2001

UK Casemix Resource Weights Project, 5th National Casemix Conference, Bristol 2000

Hospital Activity and Cost Comparisons across the Countries of the UK, PCSE 15th International Working Conference, Denmark 1999

Responding to costing and performance comparisons, Co Author Giles Pugh, The Third National Casemix Conference, Brighton 1998

Welsh Cost and Activity Analysis, Third National Casemix Conference, Brighton 1998

Welsh Cost and Activity Analysis, PCSE 14th International Working Conference, Manchester 1998

Casemix Development in Wales, The Second National Casemix Conference, Manchester 1997

Grouping Issues in England and Wales – The use of APDRGs in Wales with the Advent of HRGs Version3, PCSE 13th International Conference, Florence 1997

The Casemix Policy of England and Wales, PCSE 12th International Working Conference, Sydney 1996

The Case Mix Contracting Initiative in the NHS Wales, PCSE 11th International Working Conference, Munich 1993

S. Sutch, *The Implementation of ICD10*, PCSE 11th International Conference, Oslo 1995

EDUCATIONAL ACTIVITIES

Lecturer, Johns Hopkins Executive Education Program, 2013-2016.

Visiting Lecturer, Leids Universitair Medisch Centrum, Universiteit Leiden, Den Haag, The Netherlands, July 2016

Visiting Lecturer, School of Health Science, University of Wales Swansea, 2003-2016.

Teaching Assistant to Prof Jonathan Weiner, *Managed Care & Health Insurance*, Johns Hopkins School of Public Health, 2014, 2015

Teaching Assistant to Prof Albert Wu, *Patient Safety and Medical Errors*, Johns Hopkins School of Public Health, 2011

Advanced School Lecturer - Patient Classification System International, 2011-2016

Case Mix Funding School, Canadian Institute for Health Information (CIHI), 2015-2016

Summer School Lecturer - Patient Classification System International, 2000-2010

Member of the Faculty of Health Informatics, 2004 - 2006

Visiting Lecturer – Imperial College, London, 2004, 2005.

Visiting Lecturer - University of Occupational and Environmental Health, Kitakyusyu Japan, November 2003.

Patient Classification System Europe Committee member, 1999 – 2013, Assistant Secretary 2000-2002, Secretary 2002 – 2007, Scientific Committee 2011-2016.

Visiting Lecturer - University of Grenoble/ French Health Ministry, 1993.

Visiting Lecturer - Southbank Polytechnic, 1989.

Member of the Southampton University Operational Research M.Sc. Industrial Committee 2001 – 2008.

ADDITIONAL INFORMATION

Personal statement of research and research objectives

I have a special interest in worldwide developments in Patient Classification and its application in Health planning, funding and resource allocation. I currently specialize in population health and primary care applications of predictive models, with research interests in Care Management in Primary Care and the measurement of Multiple Morbidity. Working with the team at Johns Hopkins University (USA) on the Adjusted Clinical Groups (ACG) System, I have worked on projects in a number of countries utilizing existing primary and secondary care data to create

population based analyses, and have developed expertise in mapping differing classification systems (morbidity and pharmacy) to build whole population databases. Current projects include the development of measures for care management participation in US care plans, development of predictive models to assist English family doctors in identifying patients in the population needing outreach services, and applying the ACG System to other primary care populations in Europe and Australia.

Keywords

Care Management, Patient Participation, Multimorbidity, Case Mix Classification